Clustering_Text_Data

January 4, 2021

1 K-Means with Text Data

In this assignment you will * Cluster Wikipedia documents using k-means * Explore the role of random initialization on the quality of the clustering * Explore how results differ after changing the number of clusters * Evaluate clustering, both quantitatively and qualitatively

When properly executed, clustering uncovers valuable insights from a set of unlabeled documents.

1.1 Import Necessary Libraries

[1]:
```
import numpy as np
import pandas as pd
import os
import json
import time
import string
import sys
from scipy.sparse import csr_matrix
from sklearn.metrics.pairwise import pairwise_distances
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.preprocessing import normalize
from copy import copy
from itertools import combinations
import matplotlib.pyplot as plt
%matplotlib inline
```

1.2 Load data, extract features

[2]:
```
wiki = pd.read_csv('people_wiki.csv')
```

[3]:
```
wiki
```

[3]:
```
                                                  URI  \
0            <http://dbpedia.org/resource/Digby_Morrell>
1           <http://dbpedia.org/resource/Alfred_J._Lewy>
2            <http://dbpedia.org/resource/Harpdog_Brown>
3      <http://dbpedia.org/resource/Franz_Rottensteiner>
4                   <http://dbpedia.org/resource/G-Enka>
```

```
…                                                    …
59066          <http://dbpedia.org/resource/Olari_Elts>
59067      <http://dbpedia.org/resource/Scott_F._Crago>
59068  <http://dbpedia.org/resource/David_Cass_(footb…
59069         <http://dbpedia.org/resource/Keith_Elias>
59070        <http://dbpedia.org/resource/Fawaz_Damrah>

                           name  \
0                Digby Morrell
1               Alfred J. Lewy
2                Harpdog Brown
3          Franz Rottensteiner
4                       G-Enka
…                            …
59066              Olari Elts
59067           Scott F. Crago
59068  David Cass (footballer)
59069              Keith Elias
59070             Fawaz Damrah

                                                   text
0      digby morrell born 10 october 1979 is a former…
1      alfred j lewy aka sandy lewy graduated from un…
2      harpdog brown is a singer and harmonica player…
3      franz rottensteiner born in waidmannsfeld lowe…
4      henry krvits born 30 december 1974 in tallinn …
…                                                    …
59066  olari elts born april 27 1971 in tallinn eston…
59067  scott francis crago born july 26 1963 twin bro…
59068  david william royce cass born 27 march 1962 in…
59069  keith hector elias born february 3 1972 in lac…
59070  fawaz mohammed damrah arabic fawwz damra was t…

[59071 rows x 3 columns]
```

[4]:
```python
def load_sparse_csr(filename):
    loader = np.load(filename)
    data = loader['data']
    indices = loader['indices']
    indptr = loader['indptr']
    shape = loader['shape']
    return csr_matrix( (data, indices, indptr), shape)

tf_idf = load_sparse_csr('people_wiki_tf_idf.npz')
```

[5]:
```python
tf_idf
```

```
[5]: <59071x547979 sparse matrix of type '<class 'numpy.float64'>'
        with 10379283 stored elements in Compressed Sparse Row format>
```

```
[6]: wiki
```

```
[6]:                                                     URI  \
0              <http://dbpedia.org/resource/Digby_Morrell>
1             <http://dbpedia.org/resource/Alfred_J._Lewy>
2              <http://dbpedia.org/resource/Harpdog_Brown>
3        <http://dbpedia.org/resource/Franz_Rottensteiner>
4                     <http://dbpedia.org/resource/G-Enka>
…                                                     …
59066            <http://dbpedia.org/resource/Olari_Elts>
59067       <http://dbpedia.org/resource/Scott_F._Crago>
59068  <http://dbpedia.org/resource/David_Cass_(footb…
59069           <http://dbpedia.org/resource/Keith_Elias>
59070          <http://dbpedia.org/resource/Fawaz_Damrah>

                          name  \
0                Digby Morrell
1               Alfred J. Lewy
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3          Franz Rottensteiner
4                       G-Enka
…                          …
59066               Olari Elts
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                                                    text
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2      harpdog brown is a singer and harmonica player…
3      franz rottensteiner born in waidmannsfeld lowe…
4      henry krvits born 30 december 1974 in tallinn …
…                                                     …
59066  olari elts born april 27 1971 in tallinn eston…
59067  scott francis crago born july 26 1963 twin bro…
59068  david william royce cass born 27 march 1962 in…
59069  keith hector elias born february 3 1972 in lac…
59070  fawaz mohammed damrah arabic fawwz damra was t…

[59071 rows x 3 columns]
```

[7]:
```
with open('people_wiki_map_index_to_word.json') as people_wiki_map_index_to_word:
    map_index_to_word = json.load(people_wiki_map_index_to_word)
```

(Optional) Extracting TF-IDF vectors yourself. We provide the pre-computed TF-IDF vectors to minimize potential compatibility issues. You are free to experiment with other tools to compute the TF-IDF vectors yourself. A good place to start is sklearn.TfidfVectorizer. Note. Due to variations in tokenization and other factors, your TF-IDF vectors may differ from the ones we provide. For the purpose the assessment, we ask you to use the vectors from people_wiki_tf_idf.npz.

(Optional) Extracting TF-IDF vectors yourself. We provide the pre-computed TF-IDF vectors to minimize potential compatibility issues. You are free to experiment with other tools to compute the TF-iDF vectors yourself. A good place to start is sklearn.TfidfVectorizer. Note. Due to variations in tokenization and other factors, your TF-IDF vectors may differ from the ones we provide. For the purpose the assessment, we ask you to use the vectors from people_wiki_tf_idf.npz.

[8]:
```
def remove_punctuation(text):
    text = text.translate(str.maketrans('','',string.punctuation))

    return text

wiki['text_clean'] = wiki['text'].apply(remove_punctuation)
```

[9]:
```
vectorizer = TfidfVectorizer()

tf_idf_matrix = vectorizer.fit_transform(wiki['text_clean'])
```

[10]:
```
tf_idf_matrix
```

[10]:
```
<59071x548516 sparse matrix of type '<class 'numpy.float64'>'
        with 10243711 stored elements in Compressed Sparse Row format>
```

1.3 Normalize all Vectors

As discussed in the previous assignment, Euclidean distance can be a poor metric of similarity between documents, as it unfairly penalizes long articles. For a reasonable assessment of similarity, we should disregard the length information and use length-agnostic metrics, such as cosine distance.

The k-means algorithm does not directly work with cosine distance, so we take an alternative route to remove length information: we normalize all vectors to be unit length. It turns out that Euclidean distance closely mimics cosine distance when all vectors are unit length. In particular, the squared Euclidean distance between any two vectors of length one is directly proportional to their cosine distance.

We can prove this as follows. Let $\mathbf{x}$ and $\mathbf{y}$ be normalized vectors, i.e. unit vectors, so that $\|\mathbf{x}\| =$

$\|\mathbf{y}\| = 1$. Write the squared Euclidean distance as the dot product of $(\mathbf{x} - \mathbf{y})$ to itself:

$$\begin{aligned}
\|\mathbf{x} - \mathbf{y}\|^2 &= (\mathbf{x} - \mathbf{y})^T(\mathbf{x} - \mathbf{y}) \\
&= (\mathbf{x}^T\mathbf{x}) - 2(\mathbf{x}^T\mathbf{y}) + (\mathbf{y}^T\mathbf{y}) \\
&= \|\mathbf{x}\|^2 - 2(\mathbf{x}^T\mathbf{y}) + \|\mathbf{y}\|^2 \\
&= 2 - 2(\mathbf{x}^T\mathbf{y}) \\
&= 2(1 - (\mathbf{x}^T\mathbf{y})) \\
&= 2\left(1 - \frac{\mathbf{x}^T\mathbf{y}}{\|\mathbf{x}\|\|\mathbf{y}\|}\right) \\
&= 2\,[\text{cosine distance}]
\end{aligned}$$

This tells us that two **unit vectors** that are close in Euclidean distance are also close in cosine distance. Thus, the k-means algorithm (which naturally uses Euclidean distances) on normalized vectors will produce the same results as clustering using cosine distance as a distance metric.

We use the `normalize()` function from scikit-learn to normalize all vectors to unit length.

[11]:
```
tf_idf = normalize(tf_idf)
```

1.4 Implement k-means

Let us implement the k-means algorithm. First, we choose an initial set of centroids. A common practice is to choose randomly from the data points.

Note: We specify a seed here, so that everyone gets the same answer. In practice, we highly recommend to use different seeds every time (for instance, by using the current timestamp).

[12]:
```
def get_initial_centroids(data, k, seed=None):
    '''Randomly choose k data points as initial centroids'''
    if seed is not None: # useful for obtaining consistent results
        np.random.seed(seed)
    n = data.shape[0] # number of data points

    # Pick K indices from range [0, N).
    rand_indices = np.random.randint(0, n, k)

    # Keep centroids as dense format, as many entries will be nonzero due to␣
 ↪averaging.
    # As long as at least one document in a cluster contains a word,
    # it will carry a nonzero weight in the TF-IDF vector of the centroid.
    centroids = data[rand_indices,:].toarray()

    return centroids
```

After initialization, the k-means algorithm iterates between the following two steps: 1. Assign each data point to the closest centroid.

$$z_i \leftarrow \mathrm{argmin}_j \|\mu_j - \mathbf{x}_i\|^2$$

2. Revise centroids as the mean of the assigned data points.

$$\mu_j \leftarrow \frac{1}{n_j} \sum_{i:z_i=j} \mathbf{x}_i$$

In pseudocode, we iteratively do the following:

```
cluster_assignment = assign_clusters(data, centroids)
centroids = revise_centroids(data, k, cluster_assignment)
```

1.4.1 Assigning clusters

How do we implement Step 1 of the main k-means loop above? First import `pairwise_distances` function from scikit-learn, which calculates Euclidean distances between rows of given arrays. See this documentation for more information.

For the sake of demonstration, let's look at documents 100 through 102 as query documents and compute the distances between each of these documents and every other document in the corpus. In the k-means algorithm, we will have to compute pairwise distances between the set of centroids and the set of documents.

[13]:
```python
# Get the TF-IDF vectors for documents 100 through 102.
queries = tf_idf[100:102,:]

# Compute pairwise distances from every data point to each query vector.
dist = pairwise_distances(tf_idf, queries, metric='euclidean')

print(dist)
```

```
[[1.41000789 1.36894636]
 [1.40935215 1.41023886]
 [1.39855967 1.40890299]
 …
 [1.41108296 1.39123646]
 [1.41022804 1.31468652]
 [1.39899784 1.41072448]]
```

More formally, `dist[i,j]` is assigned the distance between the `i`th row of `X` (i.e., `X[i,:]`) and the `j`th row of `Y` (i.e., `Y[j,:]`).

Checkpoint: For a moment, suppose that we initialize three centroids with the first 3 rows of `tf_idf`. Write code to compute distances from each of the centroids to all data points in `tf_idf`. Then find the distance between row 430 of `tf_idf` and the second centroid and save it to `dist`.

[14]:
```python
queries = tf_idf[:3,:]

# Compute pairwise distances from every data point to each query vector.
dist = pairwise_distances(tf_idf, queries, metric='euclidean')[430][1]

print(dist)
```

```
1.4071310658540346
```

[15]:
```python
'''Test cell'''
if np.allclose(dist, pairwise_distances(tf_idf[430,:], tf_idf[1,:])):
    print('Pass')
else:
    print('Check your code again')
```

```
Pass
```

Checkpoint: Next, given the pairwise distances, we take the minimum of the distances for each data point. Fittingly, NumPy provides an `argmin` function. See this documentation for details.

Read the documentation and write code to produce a 1D array whose i-th entry indicates the centroid that is the closest to the i-th data point. Use the list of distances from the previous checkpoint and save them as `distances`. The value 0 indicates closeness to the first centroid, 1 indicates closeness to the second centroid, and so forth. Save this array as `closest_cluster`.

Hint: the resulting array should be as long as the number of data points.

[16]:
```python
distances = pairwise_distances(tf_idf, tf_idf[:3,:], metric='euclidean')
closest_cluster = np.argmin(distances, axis=1)
```

[17]:
```python
'''Test cell'''
reference = [list(row).index(min(row)) for row in distances]
if np.allclose(closest_cluster, reference):
    print('Pass')
else:
    print('Check your code again')
```

```
Pass
```

Checkpoint: Let's put these steps together. First, initialize three centroids with the first 3 rows of `tf_idf`. Then, compute distances from each of the centroids to all data points in `tf_idf`. Finally, use these distance calculations to compute cluster assignments and assign them to `cluster_assignment`.

[18]:
```python
centroids = tf_idf[:3,:]
distances = pairwise_distances(tf_idf, centroids, metric='euclidean')
cluster_assignment = np.argmin(distances, axis=1)
```

[19]:
```python
if len(cluster_assignment)==59071 and \
   np.array_equal(np.bincount(cluster_assignment), np.array([23061, 10086,␣
↪25924])):
    print('Pass') # count number of data points for each cluster
else:
    print('Check your code again.')
```

```
Pass
```

Now we are ready to fill in the blanks in this function:

[20]:
```python
def assign_clusters(data, centroids):

    # Compute distances between each data point and the set of centroids:
    # Fill in the blank (RHS only)
    distances_from_centroids = pairwise_distances(data, centroids,␣
 ↪metric='euclidean')

    # Compute cluster assignments for each data point:
    # Fill in the blank (RHS only)
    cluster_assignment = np.argmin(distances_from_centroids, axis=1)

    return cluster_assignment
```

which is simply generalization of what we did above.

Checkpoint. For the last time, let us check if Step 1 was implemented correctly. With rows 0, 2, 4, and 6 of `tf_idf` as an initial set of centroids, we assign cluster labels to rows 0, 10, 20, ..., and 90 of `tf_idf`. The resulting cluster labels should be `[0, 1, 1, 0, 0, 2, 0, 2, 2, 1]`.

[21]:
```python
if np.allclose(assign_clusters(tf_idf[0:100:10], tf_idf[0:8:2]), np.array([0,␣
 ↪1, 1, 0, 0, 2, 0, 2, 2, 1])):
    print('Pass')
else:
    print('Check your code again.')
```

```
Pass
```

1.4.2 Revising clusters

Let's turn to Step 2, where we compute the new centroids given the cluster assignments.

SciPy and NumPy arrays allow for filtering via Boolean masks. For instance, we filter all data points that are assigned to cluster 0 by writing

`data[cluster_assignment==0,:]`

To develop intuition about filtering, let's look at a toy example consisting of 3 data points and 2 clusters.

[22]:
```python
data = np.array([[1., 2., 0.],
                 [0., 0., 0.],
                 [2., 2., 0.]])
centroids = np.array([[0.5, 0.5, 0.],
                      [0., -0.5, 0.]])
```

Let's assign these data points to the closest centroid.

[23]:
```python
cluster_assignment = assign_clusters(data, centroids)
print(cluster_assignment)
```

```
[0 1 0]
```

The expression "cluster_assignment==1" gives a list of Booleans that says whether each data point is assigned to cluster 1 or not. For cluster 0, the expression is "cluster_assignment==0".

[24]:
```
print(cluster_assignment==1)
print(cluster_assignment==0)
```

```
[False  True False]
[ True False  True]
```

In lieu of indices, we can put in the list of Booleans to pick and choose rows. Only the rows that correspond to a True entry will be retained.

First, let's look at the data points (i.e., their values) assigned to cluster 1:

[25]:
```
print(data[cluster_assignment==1])
```

```
[[0. 0. 0.]]
```

The output makes sense since [0 0 0] is closer to [0 -0.5 0] than to [0.5 0.5 0].

Now let's look at the data points assigned to cluster 0:

[26]:
```
print(data[cluster_assignment==0])
```

```
[[1. 2. 0.]
 [2. 2. 0.]]
```

Again, this makes sense since these values are each closer to [0.5 0.5 0] than to [0 -0.5 0].

Given all the data points in a cluster, it only remains to compute the mean. Use np.mean(). By default, the function averages all elements in a 2D array. To compute row-wise or column-wise means, add the axis argument. See the linked documentation for details.

Use this function to average the data points in cluster 0:

[27]:
```
print(data[cluster_assignment==0].mean(axis=0))
```

```
[1.5 2.  0. ]
```

We are now ready to complete this function:

[28]:
```
def revise_centroids(data, k, cluster_assignment):
    new_centroids = []
    for i in range(k):
        # Select all data points that belong to cluster i. Fill in the blank␣
 ↪(RHS only)
        member_data_points = cluster_assignment==i
        # Compute the mean of the data points. Fill in the blank (RHS only)
        centroid = data[cluster_assignment==i].mean(axis=0)

        # Convert numpy.matrix type to numpy.ndarray type
        centroid = centroid.A1
        new_centroids.append(centroid)
```

```
    new_centroids = np.array(new_centroids)

    return new_centroids
```

Checkpoint. Let's check our Step 2 implementation. Letting rows 0, 10, ..., 90 of `tf_idf` as the data points and the cluster labels `[0, 1, 1, 0, 0, 2, 0, 2, 2, 1]`, we compute the next set of centroids. Each centroid is given by the average of all member data points in corresponding cluster.

[29]:
```
result = revise_centroids(tf_idf[0:100:10], 3, np.array([0, 1, 1, 0, 0, 2, 0,␣
↪2, 2, 1]))
if np.allclose(result[0], np.mean(tf_idf[[0,30,40,60]].toarray(), axis=0)) and \
   np.allclose(result[1], np.mean(tf_idf[[10,20,90]].toarray(), axis=0))   and \
   np.allclose(result[2], np.mean(tf_idf[[50,70,80]].toarray(), axis=0)):
    print('Pass')
else:
    print('Error')
```

```
Pass
```

1.4.3 Assessing convergence

How can we tell if the k-means algorithm is converging? We can look at the cluster assignments and see if they stabilize over time. In fact, we'll be running the algorithm until the cluster assignments stop changing at all. To be extra safe, and to assess the clustering performance, we'll be looking at an additional criteria: the sum of all squared distances between data points and centroids. This is defined as

$$J(\mathcal{Z}, \mu) = \sum_{j=1}^{k} \sum_{i: z_i = j} \|\mathbf{x}_i - \mu_j\|^2.$$

The smaller the distances, the more homogeneous the clusters are. In other words, we'd like to have "tight" clusters.

[30]:
```
def compute_heterogeneity(data, k, centroids, cluster_assignment):

    heterogeneity = 0.0
    for i in range(k):

        # Select all data points that belong to cluster i. Fill in the blank␣
↪(RHS only)
        member_data_points = data[cluster_assignment==i, :]

        if member_data_points.shape[0] > 0: # check if i-th cluster is non-empty
            # Compute distances from centroid to data points (RHS only)
            distances = pairwise_distances(member_data_points, [centroids[i]],␣
↪metric='euclidean')
            squared_distances = distances**2
            heterogeneity += np.sum(squared_distances)

    return heterogeneity
```

Let's compute the cluster heterogeneity for the 2-cluster example we've been considering based on our current cluster assignments and centroids.

[31]:
```python
compute_heterogeneity(data, 2, centroids, cluster_assignment)
```

[31]: 7.25

1.4.4 Combining into a single function

Once the two k-means steps have been implemented, as well as our heterogeneity metric we wish to monitor, it is only a matter of putting these functions together to write a k-means algorithm that

- Repeatedly performs Steps 1 and 2
- Tracks convergence metrics
- Stops if either no assignment changed or we reach a certain number of iterations.

[32]:
```python
# Fill in the blanks
def kmeans(data, k, initial_centroids, maxiter, record_heterogeneity=None,␣
 ↪verbose=False):
    '''This function runs k-means on given data and initial set of centroids.
       maxiter: maximum number of iterations to run.
       record_heterogeneity: (optional) a list, to store the history of␣
 ↪heterogeneity as function of iterations
                             if None, do not store the history.
       verbose: if True, print how many data points changed their cluster␣
 ↪labels in each iteration'''
    centroids = initial_centroids[:]
    prev_cluster_assignment = None

    for itr in range(maxiter):
        if verbose:
            print(itr)

        # 1. Make cluster assignments using nearest centroids
        cluster_assignment = assign_clusters(data, centroids)

        # 2. Compute a new centroid for each of the k clusters, averaging all␣
 ↪data points assigned to that cluster.
        centroids = revise_centroids(data, k, cluster_assignment)

        # Check for convergence: if none of the assignments changed, stop
        if prev_cluster_assignment is not None and \
          (prev_cluster_assignment==cluster_assignment).all():
            break

        # Print number of new assignments
        if prev_cluster_assignment is not None:
            num_changed = np.sum(prev_cluster_assignment!=cluster_assignment)
```

```
            if verbose:
                print('    {0:5d} elements changed their cluster assignment.'.
 ↪format(num_changed))

        # Record heterogeneity convergence metric
        if record_heterogeneity is not None:
            score = compute_heterogeneity(data, k, centroids,␣
 ↪cluster_assignment)
            record_heterogeneity.append(score)

        prev_cluster_assignment = cluster_assignment[:]

    return centroids, cluster_assignment
```

1.5 Plotting convergence metric

We can use the above function to plot the convergence metric across iterations.

[33]:
```
def plot_heterogeneity(heterogeneity, k):
    plt.figure(figsize=(7,4))
    plt.plot(heterogeneity, linewidth=4)
    plt.xlabel('# Iterations')
    plt.ylabel('Heterogeneity')
    plt.title('Heterogeneity of clustering over time, K={0:d}'.format(k))
    plt.rcParams.update({'font.size': 16})
    plt.tight_layout()
    plt.show()
```

Let's consider running k-means with K=3 clusters for a maximum of 400 iterations, recording cluster heterogeneity at every step. Then, let's plot the heterogeneity over iterations using the plotting function above.

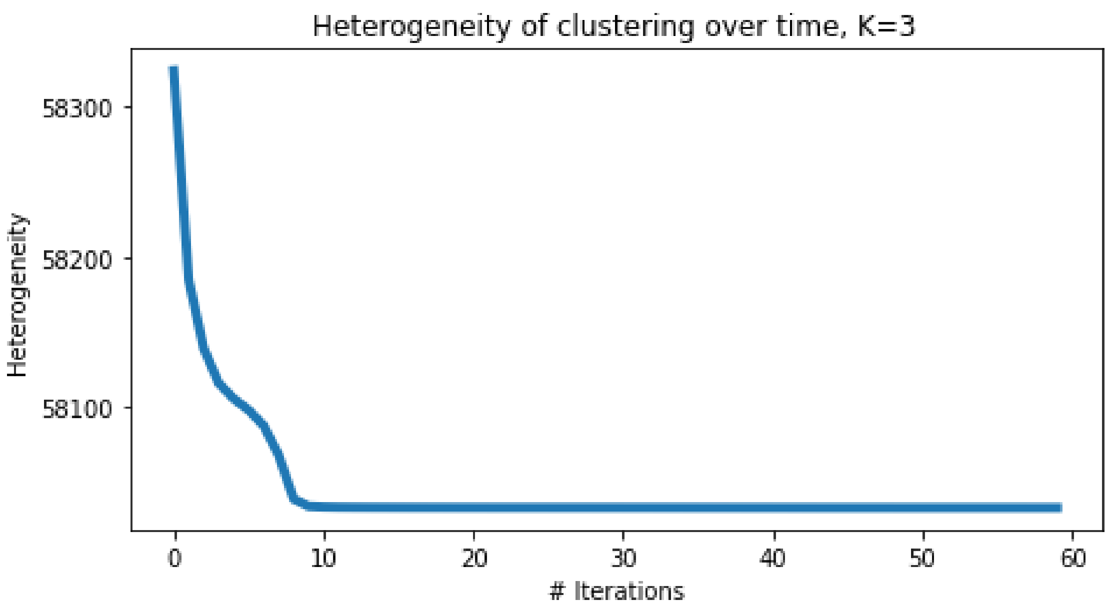
[34]:
```
k = 3
heterogeneity = []
initial_centroids = get_initial_centroids(tf_idf, k, seed=0)
centroids, cluster_assignment = kmeans(tf_idf, k, initial_centroids,␣
 ↪maxiter=400,
                                       record_heterogeneity=heterogeneity,␣
 ↪verbose=True)
plot_heterogeneity(heterogeneity, k)
```

```
0
1
    19157 elements changed their cluster assignment.
2
     7739 elements changed their cluster assignment.
3
     5119 elements changed their cluster assignment.
```

```
4
     3370 elements changed their cluster assignment.
5
     2811 elements changed their cluster assignment.
6
     3233 elements changed their cluster assignment.
7
     3815 elements changed their cluster assignment.
8
     3172 elements changed their cluster assignment.
9
     1149 elements changed their cluster assignment.
10
      498 elements changed their cluster assignment.
11
      265 elements changed their cluster assignment.
12
      149 elements changed their cluster assignment.
13
      100 elements changed their cluster assignment.
14
       76 elements changed their cluster assignment.
15
       67 elements changed their cluster assignment.
16
       51 elements changed their cluster assignment.
17
       47 elements changed their cluster assignment.
18
       40 elements changed their cluster assignment.
19
       34 elements changed their cluster assignment.
20
       35 elements changed their cluster assignment.
21
       39 elements changed their cluster assignment.
22
       24 elements changed their cluster assignment.
23
       16 elements changed their cluster assignment.
24
       12 elements changed their cluster assignment.
25
       14 elements changed their cluster assignment.
26
       17 elements changed their cluster assignment.
27
       15 elements changed their cluster assignment.
```

```
28
      14 elements changed their cluster assignment.
29
      16 elements changed their cluster assignment.
30
      21 elements changed their cluster assignment.
31
      22 elements changed their cluster assignment.
32
      33 elements changed their cluster assignment.
33
      35 elements changed their cluster assignment.
34
      39 elements changed their cluster assignment.
35
      36 elements changed their cluster assignment.
36
      36 elements changed their cluster assignment.
37
      25 elements changed their cluster assignment.
38
      27 elements changed their cluster assignment.
39
      25 elements changed their cluster assignment.
40
      28 elements changed their cluster assignment.
41
      35 elements changed their cluster assignment.
42
      31 elements changed their cluster assignment.
43
      25 elements changed their cluster assignment.
44
      18 elements changed their cluster assignment.
45
      15 elements changed their cluster assignment.
46
      10 elements changed their cluster assignment.
47
       8 elements changed their cluster assignment.
48
       8 elements changed their cluster assignment.
49
       8 elements changed their cluster assignment.
50
       7 elements changed their cluster assignment.
51
       8 elements changed their cluster assignment.
```

```
52
        3 elements changed their cluster assignment.
53
        3 elements changed their cluster assignment.
54
        4 elements changed their cluster assignment.
55
        2 elements changed their cluster assignment.
56
        3 elements changed their cluster assignment.
57
        3 elements changed their cluster assignment.
58
        1 elements changed their cluster assignment.
59
        1 elements changed their cluster assignment.
60
```



Note : It can be seen from the graph above that the clustering objective (heterogeneity) is non-increasing for this example

Note : Cluster # 2 contains the greatest number of data points in the end

1.6 Beware of local maxima

One weakness of k-means is that it tends to get stuck in a local minimum. To see this, let us run k-means multiple times, with different initial centroids created using different random seeds.

Note: Again, in practice, you should set different seeds for every run. We give you a list of seeds for this assignment so that everyone gets the same answer.

This may take several minutes to run.

[35]:
```
k = 10
heterogeneity = {}
cluster_assignment_dict = {}
start = time.time()
for seed in [0, 20000, 40000, 60000, 80000, 100000, 120000]:
    initial_centroids = get_initial_centroids(tf_idf, k, seed)
    centroids, cluster_assignment = kmeans(tf_idf, k, initial_centroids,␣
↪maxiter=400,
                                           record_heterogeneity=None,␣
↪verbose=False)
    # To save time, compute heterogeneity only once in the end
    heterogeneity[seed] = compute_heterogeneity(tf_idf, k, centroids,␣
↪cluster_assignment)

    cluster_assignment_dict[seed] = np.bincount(cluster_assignment)

#    print('seed={0:06d}, heterogeneity={1:.5f}'.format(seed,␣
↪heterogeneity[seed]))
    # And this is the modified print statement
    print('seed={0:06d}, heterogeneity={1:.5f}, cluster_distribution={2}'.
↪format(seed, heterogeneity[seed],
                                           cluster_assignment_dict[seed]))
    sys.stdout.flush()
end = time.time()

print('\n' + str(end-start))


print('\n\n==========================================================================\n\n'

k = 10
heterogeneity = {}
max_values = []
min_values = []
start = time.time()
for seed in [0, 20000, 40000, 60000, 80000, 100000, 120000]:
    initial_centroids = get_initial_centroids(tf_idf, k, seed)
    centroids, cluster_assignment = kmeans(tf_idf, k, initial_centroids,␣
↪maxiter=400,
                                           record_heterogeneity=None,␣
↪verbose=False)

    bin_array = np.bincount(cluster_assignment)
```

```
    idx = np.argmax(bin_array)
    val = bin_array[idx]
    print('seed :', seed, '\tmax_idx :', '\tmax_val :', val)
    max_values.append(val)

    idx = np.argmin(bin_array)
    val = bin_array[idx]
    print('seed :', seed, '\tmin_idx :', '\tmin_val :', val)
    min_values.append(val)

    # To save time, compute heterogeneity only once in the end
    heterogeneity[seed] = compute_heterogeneity(tf_idf, k, centroids,␣
↪cluster_assignment)
    print('seed :', seed, '\theterogeneity :', heterogeneity[seed])
    print('\n')
    sys.stdout.flush()

end = time.time()
total_time = end - start

max_value = max(max_values)
min_value = min(min_values)

print('Max Value :', max_value)
print('Min Value :', min_value)

print('\n' + str(total_time))
```

```
seed=000000, heterogeneity=57457.52442, cluster_distribution=[18047  3824  5671
6983  1492  1730  3882  3449  7139  6854]
seed=020000, heterogeneity=57533.20100, cluster_distribution=[ 3142   768  3566
2277 15779  7278  6146  7964  6666  5485]
seed=040000, heterogeneity=57512.69257, cluster_distribution=[ 5551  6623   186
2999  8487  3893  6807  2921  3472 18132]
seed=060000, heterogeneity=57466.97925, cluster_distribution=[ 3014  3089  6681
3856  8080  7222  3424   424  5381 17900]
seed=080000, heterogeneity=57494.92990, cluster_distribution=[17582  1785  7215
3314  6285   809  5930  6791  5536  3824]
seed=100000, heterogeneity=57484.42210, cluster_distribution=[ 6618  1337  6191
2890 16969  4983  5242  3892  5562  5387]
seed=120000, heterogeneity=57554.62410, cluster_distribution=[ 6118  5841  4964
8423  4302  3183 16481  1608  5524  2627]

127.81221437454224
```

==

```
seed : 0        max_idx :       max_val : 18047
seed : 0        min_idx :       min_val : 1492
seed : 0        heterogeneity : 57457.52442292027


seed : 20000    max_idx :       max_val : 15779
seed : 20000    min_idx :       min_val : 768
seed : 20000    heterogeneity : 57533.20099687315


seed : 40000    max_idx :       max_val : 18132
seed : 40000    min_idx :       min_val : 186
seed : 40000    heterogeneity : 57512.692572562795


seed : 60000    max_idx :       max_val : 17900
seed : 60000    min_idx :       min_val : 424
seed : 60000    heterogeneity : 57466.97924645124


seed : 80000    max_idx :       max_val : 17582
seed : 80000    min_idx :       min_val : 809
seed : 80000    heterogeneity : 57494.92989694541


seed : 100000   max_idx :       max_val : 16969
seed : 100000   min_idx :       min_val : 1337
seed : 100000   heterogeneity : 57484.42209612294


seed : 120000   max_idx :       max_val : 16481
seed : 120000   min_idx :       min_val : 1608
seed : 120000   heterogeneity : 57554.624099931665


Max Value : 18132
Min Value : 186
```

```
123.34868955612183
```

Notice the variation in heterogeneity for different initializations. This indicates that k-means sometimes gets stuck at a bad local minimum.

Note : Another way to capture the effect of changing initialization is to look at the distribution of cluster assignments. Looking at the size of the largest cluster (most # of member data points) across multiple runs, with seeds 0, 20000, ..., 120000. The minimum value this quantity takes is ___ and maximum values this quantity takes is ___

One effective way to counter this tendency is to use **k-means++** to provide a smart initialization. This method tries to spread out the initial set of centroids so that they are not too close together. It is known to improve the quality of local optima and lower average runtime.

[36]:
```
def smart_initialize(data, k, seed=None):
    '''Use k-means++ to initialize a good set of centroids'''
    if seed is not None: # useful for obtaining consistent results
        np.random.seed(seed)
    centroids = np.zeros((k, data.shape[1]))

    # Randomly choose the first centroid.
    # Since we have no prior knowledge, choose uniformly at random
    idx = np.random.randint(data.shape[0])
    centroids[0] = data[idx,:].toarray()
    # Compute distances from the first centroid chosen to all the other data␣
 ↪points
    squared_distances = pairwise_distances(data, centroids[0:1],␣
 ↪metric='euclidean').flatten()**2

    for i in range(1, k):
        # Choose the next centroid randomly, so that the probability for each␣
 ↪data point to be chosen
        # is directly proportional to its squared distance from the nearest␣
 ↪centroid.
        # Roughtly speaking, a new centroid should be as far as from ohter␣
 ↪centroids as possible.
        idx = np.random.choice(data.shape[0], 1, p=squared_distances/
 ↪sum(squared_distances))
        centroids[i] = data[idx,:].toarray()
        # Now compute distances from the centroids to all data points
        squared_distances = np.min(pairwise_distances(data, centroids[0:i+1],␣
 ↪metric='euclidean')**2,axis=1)

    return centroids
```

Let's now rerun k-means with 10 clusters using the same set of seeds, but always using k-means++ to initialize the algorithm.

This may take several minutes to run.

[37]:
```
k = 10
heterogeneity_smart = {}
seeds = [0, 20000, 40000, 60000, 80000, 100000, 120000]
for seed in seeds:
    initial_centroids = smart_initialize(tf_idf, k, seed)
    centroids, cluster_assignment = kmeans(tf_idf, k, initial_centroids,␣
 ↪maxiter=400,
```

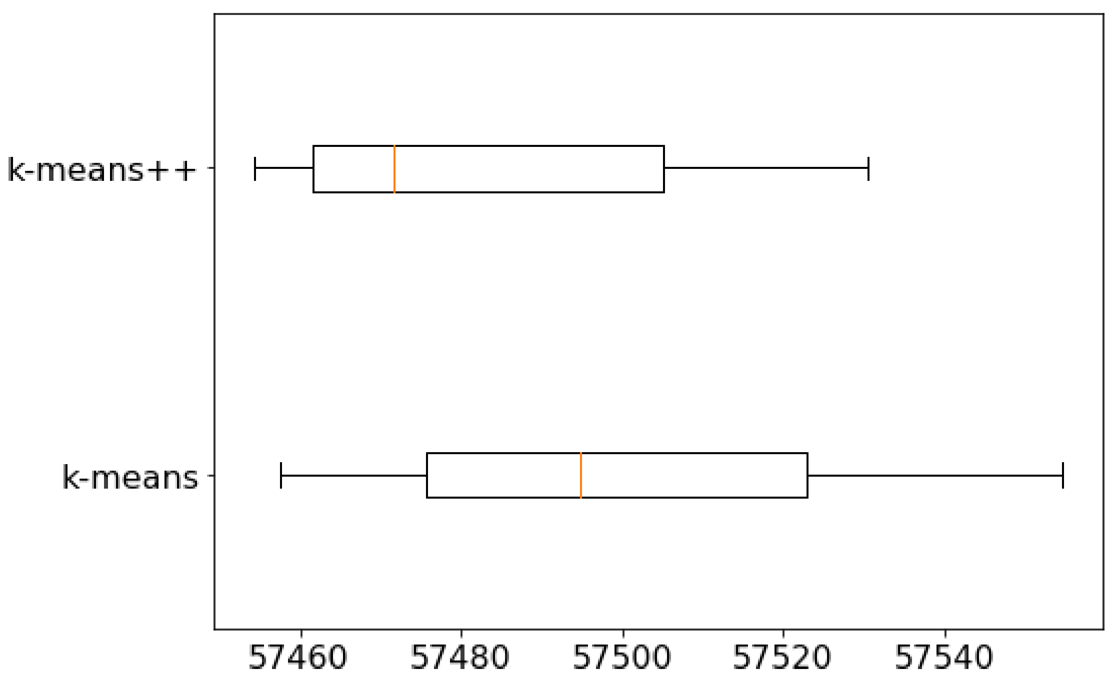
```
                                                         record_heterogeneity=None,␣
↪verbose=False)
    # To save time, compute heterogeneity only once in the end
    heterogeneity_smart[seed] = compute_heterogeneity(tf_idf, k, centroids,␣
↪cluster_assignment)
    print('seed={0:06d}, heterogeneity={1:.5f}'.format(seed,␣
↪heterogeneity_smart[seed]))
    sys.stdout.flush()
```

```
seed=000000, heterogeneity=57468.63808
seed=020000, heterogeneity=57486.94263
seed=040000, heterogeneity=57454.35926
seed=060000, heterogeneity=57530.43659
seed=080000, heterogeneity=57454.51852
seed=100000, heterogeneity=57471.56674
seed=120000, heterogeneity=57523.28839
```

Let's compare the set of cluster heterogeneities we got from our 7 restarts of k-means using random initialization compared to the 7 restarts of k-means using k-means++ as a smart initialization.

The following code produces a box plot for each of these methods, indicating the spread of values produced by each method.

[38]:
```
plt.figure(figsize=(8,5))
plt.boxplot([list(heterogeneity.values()), list(heterogeneity_smart.values())],␣
 ↪vert=False)
plt.yticks([1, 2], ['k-means', 'k-means++'])
plt.rcParams.update({'font.size': 16})
plt.tight_layout()
```



A few things to notice from the box plot: * On average, k-means++ produces a better clustering than Random initialization. * Variation in clustering quality is smaller for k-means++.

In general, you should run k-means at least a few times with different initializations and then return the run resulting in the lowest heterogeneity. Let us write a function that runs k-means multiple times and picks the best run that minimizes heterogeneity. The function accepts an optional list of seed values to be used for the multiple runs; if no such list is provided, the current UTC time is used as seed values.

[39]:
```
def kmeans_multiple_runs(data, k, maxiter, num_runs, seed_list=None,␣
↪verbose=False):
    heterogeneity = {}

    min_heterogeneity_achieved = float('inf')
    best_seed = None
    final_centroids = None
    final_cluster_assignment = None

    for i in xrange(num_runs):

        # Use UTC time if no seeds are provided
        if seed_list is not None:
            seed = seed_list[i]
            np.random.seed(seed)
        else:
            seed = int(time.time())
            np.random.seed(seed)

        # Use k-means++ initialization
        initial_centroids = smart_initialize(data, k, seed)

        # Run k-means
        centroids, cluster_assignment = kmeans(data, k, initial_centroids,␣
↪maxiter, record_heterogeneity=None, verbose=False)

        # To save time, compute heterogeneity only once in the end"
        heterogeneity[seed] = compute_heterogeneity(data, k, centroids,␣
↪cluster_assignment)

        if verbose:
            print('seed={0:06d}, heterogeneity={1:.5f}'.format(seed,␣
↪heterogeneity[seed]))
            sys.stdout.flush()

        # if current measurement of heterogeneity is lower than previously seen,
```

```
        # update the minimum record of heterogeneity.
        if heterogeneity[seed] < min_heterogeneity_achieved:
            min_heterogeneity_achieved = heterogeneity[seed]
            best_seed = seed
            final_centroids = centroids
            final_cluster_assignment = cluster_assignment

    # Return the centroids and cluster assignments that minimize heterogeneity.
    return final_centroids, final_cluster_assignment
```

1.7 How to choose K

Since we are measuring the tightness of the clusters, a higher value of K reduces the possible heterogeneity metric by definition. For example, if we have N data points and set K=N clusters, then we could have 0 cluster heterogeneity by setting the N centroids equal to the values of the N data points. (Note: Not all runs for larger K will result in lower heterogeneity than a single run with smaller K due to local optima.) Let's explore this general trend for ourselves by performing the following analysis.

Use the `kmeans_multiple_runs` function to run k-means with five different values of K. For each K, use k-means++ and multiple runs to pick the best solution. In what follows, we consider K=2,10,25,50,100 and 7 restarts for each setting.

IMPORTANT: The code block below will take about 10 minutes to finish

In order to speed up the computations, we run them with only one random seed, but for better performance, one should use more seeds and compare the results. If you don't mind running the code for approximately one hour, feel free to uncomment the following line of code below:

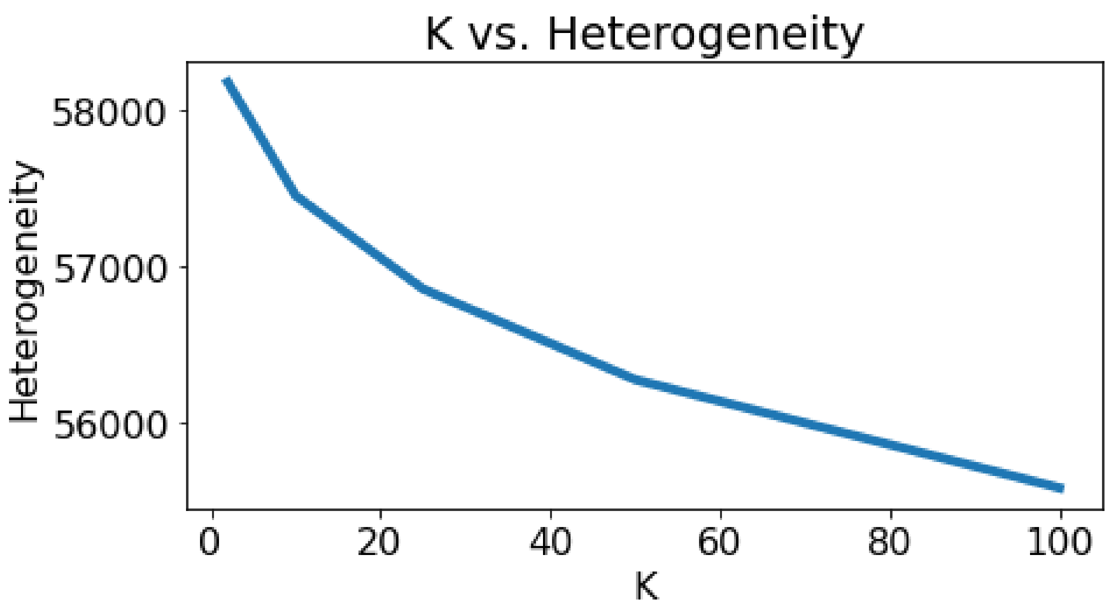
`seed_list = [0]#, 20000, 40000, 60000, 80000, 100000, 120000]`

Side note: In practice, a good implementation of k-means would utilize parallelism to run multiple runs of k-means at once. For an example, see scikit-learn's KMeans.

[40]:
```
def plot_k_vs_heterogeneity(k_values, heterogeneity_values):
    plt.figure(figsize=(7,4))
    plt.plot(k_values, heterogeneity_values, linewidth=4)
    plt.xlabel('K')
    plt.ylabel('Heterogeneity')
    plt.title('K vs. Heterogeneity')
    plt.rcParams.update({'font.size': 16})
    plt.tight_layout()

filename = 'kmeans-arrays.npz'

heterogeneity_values = []
k_list = [2, 10, 25, 50, 100]

if os.path.exists(filename):
    arrays = np.load(filename)
```

```
    centroids = {}
    cluster_assignment = {}
    for k in k_list:
        print(k)
        sys.stdout.flush()
        '''To save memory space, do not load the arrays from the file right␣
↪away. We use
           a technique known as lazy evaluation, where some expressions are not␣
↪evaluated
           until later. Any expression appearing inside a lambda function␣
↪doesn't get
           evaluated until the function is called.
           Lazy evaluation is extremely important in memory-constrained␣
↪setting, such as
           an Amazon EC2 t2.micro instance.'''
        centroids[k] = lambda k=k: arrays['centroids_{0:d}'.format(k)]
        cluster_assignment[k] = lambda k=k: arrays['cluster_assignment_{0:d}'.
↪format(k)]
        score = compute_heterogeneity(tf_idf, k, centroids[k](),␣
↪cluster_assignment[k]())
        heterogeneity_values.append(score)

    plot_k_vs_heterogeneity(k_list, heterogeneity_values)

else:
    print('File not found. Skipping.')
```

```
2
10
25
50
100
```



In the above plot we show that heterogeneity goes down as we increase the number of clusters. Does this mean we should always favor a higher K? **Not at all!** As we will see in the following section, setting K too high may end up separating data points that are actually pretty alike. At the extreme, we can set individual data points to be their own clusters (K=N) and achieve zero heterogeneity, but separating each data point into its own cluster is hardly a desirable outcome. In the following section, we will learn how to detect a K set "too large".

1.8 Visualize clusters of documents

Let's start visualizing some clustering results to see if we think the clustering makes sense. We can use such visualizations to help us assess whether we have set K too large or too small for a given application. Following the theme of this course, we will judge whether the clustering makes sense in the context of document analysis.

What are we looking for in a good clustering of documents? * Documents in the same cluster should be similar. * Documents from different clusters should be less similar.

So a bad clustering exhibits either of two symptoms: * Documents in a cluster have mixed content. * Documents with similar content are divided up and put into different clusters.

To help visualize the clustering, we do the following: * Fetch nearest neighbors of each centroid from the set of documents assigned to that cluster. We will consider these documents as being representative of the cluster. * Print titles and first sentences of those nearest neighbors. * Print top 5 words that have highest tf-idf weights in each centroid.

[41]:
```
map_index_to_word = pd.DataFrame(map_index_to_word.items(),␣
↪columns=['category', 'index'])
```

```
[42]: def visualize_document_clusters(wiki, tf_idf, centroids, cluster_assignment, k,␣
    ↪map_index_to_word, display_content=True):
        '''wiki: original dataframe
           tf_idf: data matrix, sparse matrix format
           map_index_to_word: SFrame specifying the mapping betweeen words and␣
    ↪column indices
           display_content: if True, display 8 nearest neighbors of each centroid'''

        print('==========================================================')

        # Visualize each cluster c
        for c in range(k):
            # Cluster heading
            print('Cluster {0:d}    '.format(c)),
            # Print top 5 words with largest TF-IDF weights in the cluster
            idx = centroids[c].argsort()[::-1]
            for i in range(5): # Print each word along with the TF-IDF weight
                print('{0:s}:{1:.3f}'.format(map_index_to_word['category'][idx[i]],␣
    ↪centroids[c,idx[i]])),
            print('')

            if display_content:
                # Compute distances from the centroid to all data points in the␣
    ↪cluster,
                # and compute nearest neighbors of the centroids within the cluster.
                distances = pairwise_distances(tf_idf, centroids[c].reshape(1, -1),␣
    ↪metric='euclidean').flatten()
                distances[cluster_assignment!=c] = float('inf') # remove␣
    ↪non-members from consideration
                nearest_neighbors = distances.argsort()
                # For 8 nearest neighbors, print the title as well as first 180␣
    ↪characters of text.
                # Wrap the text at 80-character mark.
                for i in range(8):
                    text = ' '.join(wiki.iloc[nearest_neighbors[i]]['text'].
    ↪split(None, 25)[0:25])
                    print('\n* {0:50s} {1:.5f}\n  {2:s}\n  {3:s}'.format(wiki.
    ↪iloc[nearest_neighbors[i]]['name'],
                        distances[nearest_neighbors[i]], text[:90], text[90:180] if␣
    ↪len(text) > 90 else ''))
            print('==========================================================')
```

Let us first look at the 2 cluster case (K=2).

```
[43]: visualize_document_clusters(wiki, tf_idf, centroids[2](),␣
    ↪cluster_assignment[2](), 2, map_index_to_word)
```

```
==========================================================
Cluster 0
serieslong:0.025
bostonas:0.017
33story:0.012
gan:0.011
efovi:0.011


* Anita Kunz                                          0.97401
  anita e kunz oc born 1956 is a canadianborn artist and illustratorkunz has
lived in london
   new york and toronto contributing to magazines and working

* Janet Jackson                                       0.97472
  janet damita jo jackson born may 16 1966 is an american singer songwriter and
actress know
  n for a series of sonically innovative socially conscious and

* Madonna (entertainer)                               0.97475
  madonna louise ciccone tkoni born august 16 1958 is an american singer
songwriter actress
  and businesswoman she achieved popularity by pushing the boundaries of lyrical

* %C3%81ine Hyland                                    0.97536
  ine hyland ne donlon is emeritus professor of education and former
vicepresident of univer
  sity college cork ireland she was born in 1942 in athboy co

* Jane Fonda                                          0.97621
  jane fonda born lady jayne seymour fonda december 21 1937 is an american
actress writer po
  litical activist former fashion model and fitness guru she is

* Christine Robertson                                 0.97643
  christine mary robertson born 5 october 1948 is an australian politician and
former austra
  lian labor party member of the new south wales legislative council serving

* Pat Studdy-Clift                                    0.97643
  pat studdyclift is an australian author specialising in historical fiction and
nonfictionb
  orn in 1925 she lived in gunnedah until she was sent to a boarding

* Alexandra Potter                                    0.97646
  alexandra potter born 1970 is a british author of romantic comediesborn in
bradford yorksh
  ire england and educated at liverpool university gaining an honors degree in
```

```
==========================================================
Cluster 1
19771992according:0.040
sibinki:0.036
gonino:0.029
anchoragearea:0.029
ngandu:0.028


* Todd Williams                                      0.95468
  todd michael williams born february 13 1971 in syracuse new york is a former
major league
  baseball relief pitcher he attended east syracuseminoa high school

* Gord Sherven                                       0.95622
  gordon r sherven born august 21 1963 in gravelbourg saskatchewan and raised in
mankota sas
  katchewan is a retired canadian professional ice hockey forward who played

* Justin Knoedler                                    0.95639
  justin joseph knoedler born july 17 1980 in springfield illinois is a former
major league
  baseball catcherknoedler was originally drafted by the st louis cardinals

* Chris Day                                          0.95648
  christopher nicholas chris day born 28 july 1975 is an english professional
footballer who
   plays as a goalkeeper for stevenageday started his career at tottenham

* Tony Smith (footballer, born 1957)                 0.95653
  anthony tony smith born 20 february 1957 is a former footballer who played as
a central de
  fender in the football league in the 1970s and

* Ashley Prescott                                    0.95761
  ashley prescott born 11 september 1972 is a former australian rules footballer
he played w
  ith the richmond and fremantle football clubs in the afl between

* Leslie Lea                                         0.95802
  leslie lea born 5 october 1942 in manchester is an english former professional
footballer
  he played as a midfielderlea began his professional career with blackpool

* Tommy Anderson (footballer)                        0.95818
  thomas cowan tommy anderson born 24 september 1934 in haddington is a scottish
former prof
  essional footballer he played as a forward and was noted for
```

```
==========================================================
```

Both clusters have mixed content, although cluster 1 is much purer than cluster 0: * Cluster 0: academia, law * Cluster 1: female figures, baseball players

Roughly speaking, the entire dataset was divided into athletes and non-athletes. It would be better if we sub-divided non-atheletes into more categories. So let us use more clusters. How about `K=10`?

[44]:
```
k = 10
visualize_document_clusters(wiki, tf_idf, centroids[k](),␣
 ↪cluster_assignment[k](), k, map_index_to_word)
```

```
==========================================================
Cluster 0
allmvfc:0.020
scientistagreed:0.014
gan:0.011
psihomodo:0.010
2001pasithee:0.010


* Wilson McLean                                      0.97479
  wilson mclean born 1937 is a scottish illustrator and artist he has
illustrated primarily
  in the field of advertising but has also provided cover art

* Anton Hecht                                        0.97748
  anton hecht is an english artist born in london in 2007 he asked musicians
from around the
   durham area to contribute to a soundtrack for

* David Salle                                        0.97800
  david salle born 1952 is an american painter printmaker and stage designer who
helped defi
  ne postmodern sensibility salle was born in norman oklahoma he earned

* Vipin Sharma                                       0.97805
  vipin sharma is an indian actor born in new delhi he is a graduate of national
school of d
  rama new delhi india and the canadian

* Paul Swadel                                        0.97823
  paul swadel is a new zealand film director and producerhe has directed and
produced many s
  uccessful short films which have screened in competition at cannes

* Allan Stratton                                     0.97834
  allan stratton born 1951 is a canadian playwright and novelistborn in
stratford ontario st
```

```
  ratton began his professional arts career while he was still in high

* Bill Bennett (director)                              0.97848
  bill bennett born 1953 is an australian film director producer and
screenwriterhe dropped
  out of medicine at queensland university in 1972 and joined the australian

* Rafal Zielinski                                      0.97850
  rafal zielinski born 1957 montreal is an independent filmmaker he is best
known for direct
  ing films such as fun sundance film festival special jury award
==========================================================
Cluster 1
19771992according:0.052
famekarl:0.044
5153:0.042
legislaturewhen:0.042
sibinki:0.041


* Chris Day                                            0.93220
  christopher nicholas chris day born 28 july 1975 is an english professional
footballer who
   plays as a goalkeeper for stevenageday started his career at tottenham

* Gary Hooper                                          0.93481
  gary hooper born 26 january 1988 is an english professional footballer who
plays as a forw
  ard for norwich cityhooper started his career at nonleague grays

* Tony Smith (footballer, born 1957)                   0.93504
  anthony tony smith born 20 february 1957 is a former footballer who played as
a central de
  fender in the football league in the 1970s and

* Jason Roberts (footballer)                           0.93527
  jason andre davis roberts mbe born 25 january 1978 is a former professional
footballer and
   now a football punditborn in park royal london roberts was

* Paul Robinson (footballer, born 1979)                0.93587
  paul william robinson born 15 october 1979 is an english professional
footballer who plays
   for blackburn rovers as a goalkeeper he is a former england

* Alex Lawless                                         0.93732
  alexander graham alex lawless born 26 march 1985 is a welsh professional
footballer who pl
```

ays for luton town as a midfielderlawless began his career with

* Neil Grayson 0.93748
  neil grayson born 1 november 1964 in york is an english footballer who last played as a st
  riker for sutton towngraysons first club was local

* Sol Campbell 0.93759
  sulzeer jeremiah sol campbell born 18 september 1974 is a former england international foo
  tballer a central defender he had a 19year career playing in the

==

Cluster 2
agency:0.040
ebe:0.037
qafl:0.032
addaction:0.029
spanky:0.029

* Alessandra Aguilar 0.94505
  alessandra aguilar born 1 july 1978 in lugo is a spanish longdistance runner who specialis
  es in marathon running she represented her country in the event

* Heather Samuel 0.94529
  heather barbara samuel born 6 july 1970 is a retired sprinter from antigua and barbuda who
  specialized in the 100 and 200 metres in 1990

* Viola Kibiwot 0.94617
  viola jelagat kibiwot born december 22 1983 in keiyo district is a runner from kenya who s
  pecialises in the 1500 metres kibiwot won her first

* Ayelech Worku 0.94636
  ayelech worku born june 12 1979 is an ethiopian longdistance runner most known for winning
  two world championships bronze medals on the 5000 metres she

* Morhad Amdouni 0.94763
  morhad amdouni born 21 january 1988 in portovecchio is a french middle and longdistance ru
  nner he was european junior champion in track and cross country

* Krisztina Papp 0.94776
  krisztina papp born 17 december 1982 in eger is a hungarian long distance runner she is th

```
  e national indoor record holder over 5000 mpapp began

* Petra Lammert                                     0.94869
  petra lammert born 3 march 1984 in freudenstadt badenwrttemberg is a former
german shot pu
  tter and current bobsledder she was the 2009 european indoor champion

* Hasan Mahboob                                     0.94880
  hasan mahboob ali born silas kirui on 31 december 1981 in kapsabet is a
bahraini longdista
  nce runner he became naturalized in bahrain and switched from
==========================================================
Cluster 3
qc:0.110
19771992according:0.103
aulas:0.052
guitarscordray:0.047
sibinki:0.045


* Steve Springer                                    0.89300
  steven michael springer born february 11 1961 is an american former
professional baseball
  player who appeared in major league baseball as a third baseman and

* Dave Ford                                         0.89547
  david alan ford born december 29 1956 is a former major league baseball
pitcher for the ba
  ltimore orioles born in cleveland ohio ford attended lincolnwest

* Todd Williams                                     0.89820
  todd michael williams born february 13 1971 in syracuse new york is a former
major league
  baseball relief pitcher he attended east syracuseminoa high school

* Justin Knoedler                                   0.90035
  justin joseph knoedler born july 17 1980 in springfield illinois is a former
major league
  baseball catcherknoedler was originally drafted by the st louis cardinals

* Kevin Nicholson (baseball)                        0.90643
  kevin ronald nicholson born march 29 1976 is a canadian baseball shortstop he
played part
  of the 2000 season for the san diego padres of

* James Baldwin (baseball)                          0.90648
  james j baldwin jr born july 15 1971 is a former major league baseball pitcher
he batted a
```

```
  nd threw righthanded in his 11season career he

* Joe Strong                                          0.90655
  joseph benjamin strong born september 9 1962 in fairfield california is a
former major lea
  gue baseball pitcher who played for the florida marlins from 2000

* Javier L%C3%B3pez (baseball)                        0.90691
  javier alfonso lpez born july 11 1977 is a puerto rican professional baseball
pitcher for
  the san francisco giants of major league baseball he is
==========================================================
Cluster 4
preposition:0.038
efovi:0.035
2210:0.032
hundreaarsvisningen:0.023
jrwho:0.019


* Lawrence W. Green                                   0.95957
  lawrence w green is best known by health education researchers as the
originator of the pr
  ecede model and codeveloper of the precedeproceed model which has

* Timothy Luke                                        0.96057
  timothy w luke is university distinguished professor of political science in
the college o
  f liberal arts and human sciences as well as program chair of

* Ren%C3%A9e Fox                                       0.96100
  rene c fox a summa cum laude graduate of smith college in 1949 earned her phd
in sociology
   in 1954 from radcliffe college harvard university

* Francis Gavin                                       0.96323
  francis j gavin is first frank stanton chair in nuclear security policy
studies and profes
  sor of political science at mit before joining mit he was

* Catherine Hakim                                     0.96374
  catherine hakim born 30 may 1948 is a british sociologist who specialises in
womens employ
  ment and womens issues she is currently a professorial research fellow

* Stephen Park Turner                                 0.96405
  stephen turner is a researcher in social practice social and political theory
and the phil
```

```
  osophy of the social sciences he is graduate research professor in

* Robert Bates (political scientist)                0.96489
  robert hinrichs bates born 1942 is an american political scientist he is eaton
professor o
  f the science of government in the departments of government and

* Georg von Krogh                                   0.96505
  georg von krogh was born in oslo norway he is a professor at eth zurich and
holds the chai
  r of strategic management and innovation he
==========================================================
Cluster 5
anchoragearea:0.076
ssls:0.060
eros1988:0.056
sibinki:0.044
ngandu:0.037


* Todd Curley                                       0.92731
  todd curley born 14 january 1973 is a former australian rules footballer who
played for co
  llingwood and the western bulldogs in the australian football league

* Ashley Prescott                                   0.92992
  ashley prescott born 11 september 1972 is a former australian rules footballer
he played w
  ith the richmond and fremantle football clubs in the afl between

* Pete Richardson                                   0.93204
  pete richardson born october 17 1946 in youngstown ohio is a former american
football defe
  nsive back in the national football league and former college head

* Nathan Brown (Australian footballer born 1976)     0.93561
  nathan daniel brown born 14 august 1976 is an australian rules footballer who
played for t
  he melbourne demons in the australian football leaguehe was drafted

* Earl Spalding                                     0.93654
  earl spalding born 11 march 1965 in south perth is a former australian rules
footballer wh
  o played for melbourne and carlton in the victorian football

* Bud Grant                                         0.93766
  harry peter bud grant jr born may 20 1927 is a former american football and
canadian footb
```

```
  all head coach grant served as the head coach

* Tyrone Wheatley                                    0.93885
  tyrone anthony wheatley born january 19 1972 is the running backs coach of
michigan and a
  former professional american football player who played 10 seasons

* Nick Salter                                        0.93916
  nick salter born 30 july 1987 is an australian rules footballer who played for
port adelai
  de football club in the australian football league aflhe was
==========================================================
Cluster 6
serieslong:0.138
bostonas:0.089
interlingual:0.014
allmvfc:0.013
fons:0.012


* Lauren Royal                                       0.93445
  lauren royal born march 3 circa 1965 is a book writer from california royal
has written bo
  th historic and novelistic booksa selfproclaimed angels baseball fan

* Barbara Hershey                                    0.93496
  barbara hershey born barbara lynn herzstein february 5 1948 once known as
barbara seagull
  is an american actress in a career spanning nearly 50 years

* Janet Jackson                                      0.93559
  janet damita jo jackson born may 16 1966 is an american singer songwriter and
actress know
  n for a series of sonically innovative socially conscious and

* Jane Fonda                                         0.93759
  jane fonda born lady jayne seymour fonda december 21 1937 is an american
actress writer po
  litical activist former fashion model and fitness guru she is

* Janine Shepherd                                    0.93833
  janine lee shepherd am born 1962 is an australian pilot and former
crosscountry skier shep
  herds career as an athlete ended when she suffered major injuries

* Ellina Graypel                                     0.93847
  ellina graypel born july 19 1972 is an awardwinning russian singersongwriter
she was born
```

```
  near the volga river in the heart of russia she spent

* Alexandra Potter                                   0.93858
  alexandra potter born 1970 is a british author of romantic comediesborn in
bradford yorksh
  ire england and educated at liverpool university gaining an honors degree in

* Melissa Hart (actress)                             0.93913
  melissa hart is an american actress singer and teacher she made her broadway
debut in 1966
   as an ensemble member in jerry bocks the apple
==========================================================
Cluster 7
33story:0.057
conder:0.040
nanri:0.035
burkewhite:0.023
1975one:0.022


* Brenton Broadstock                                 0.95722
  brenton broadstock ao born 1952 is an australian composerbroadstock was born
in melbourne
  he studied history politics and music at monash university and later
composition

* Prince (musician)                                  0.96057
  prince rogers nelson born june 7 1958 known by his mononym prince is an
american singerson
  gwriter multiinstrumentalist and actor he has produced ten platinum albums

* Will.i.am                                          0.96066
  william adams born march 15 1975 known by his stage name william pronounced
will i am is a
  n american rapper songwriter entrepreneur actor dj record

* Tom Bancroft                                       0.96117
  tom bancroft born 1967 london is a british jazz drummer and composer he began
drumming age
  d seven and started off playing jazz with his father

* Julian Knowles                                     0.96152
  julian knowles is an australian composer and performer specialising in new and
emerging te
  chnologies his creative work spans the fields of composition for theatre dance

* Dan Siegel (musician)                              0.96223
  dan siegel born in seattle washington is a pianist composer and record
```

```
producer his earlie
  r music has been described as new age while his more

* Tony Mills (musician)                              0.96238
  tony mills born 7 july 1962 in solihull england is an english rock singer best
known for h
  is work with shy and tnthailing from birmingham

* Don Robertson (composer)                           0.96249
  don robertson born 1942 is an american composerdon robertson was born in 1942
in denver co
  lorado and began studying music with conductor and pianist antonia
==========================================================
Cluster 8
ibnez:0.216
jeffnominated:0.134
usyd:0.065
sibinki:0.053
19771992according:0.047


* Gord Sherven                                       0.83598
  gordon r sherven born august 21 1963 in gravelbourg saskatchewan and raised in
mankota sas
  katchewan is a retired canadian professional ice hockey forward who played

* Eric Brewer                                        0.83765
  eric peter brewer born april 17 1979 is a canadian professional ice hockey
defenceman for
  the anaheim ducks of the national hockey league nhl he

* Stephen Johns (ice hockey)                         0.84580
  stephen johns born april 18 1992 is an american professional ice hockey
defenceman he is c
  urrently playing with the rockford icehogs of the american hockey

* Mike Stevens (ice hockey, born 1965)               0.85320
  mike stevens born december 30 1965 in kitchener ontario is a retired
professional ice hock
  ey player who played 23 games in the national hockey league

* Tanner Glass                                       0.85484
  tanner glass born november 29 1983 is a canadian professional ice hockey
winger who plays
  for the new york rangers of the national hockey league

* Todd Strueby                                       0.86053
  todd kenneth strueby born june 15 1963 in lanigan saskatchewan and raised in
```

humboldt sask
  atchewan is a retired canadian professional ice hockey centre who played

* Steven King (ice hockey)   0.86129
  steven andrew king born july 22 1969 in east greenwich rhode island is a
former ice hockey
   forward who played professionally from 1991 to 2000

* Don Jackson (ice hockey)   0.86661
  donald clinton jackson born september 2 1956 in minneapolis minnesota and
bloomington minn
  esota is an ice hockey coach and a retired professional ice hockey player
==
Cluster 9
zahida:0.028
pricepottenger:0.025
lopilato:0.025
reapersince:0.021
blitzattack:0.019

* Doug Lewis   0.96516
  douglas grinslade doug lewis pc qc born april 17 1938 is a former canadian
politician a ch
  artered accountant and lawyer by training lewis entered the

* David Anderson (British Columbia politician)   0.96530
  david a anderson pc oc born august 16 1937 in victoria british columbia is a
former canadi
  an cabinet minister educated at victoria college in victoria

* Lucienne Robillard   0.96679
  lucienne robillard pc born june 16 1945 is a canadian politician and a member
of the liber
  al party of canada she sat in the house

* Bob Menendez   0.96686
  robert bob menendez born january 1 1954 is the senior united states senator
from new jerse
  y he is a member of the democratic party first

* Mal Sandon   0.96706
  malcolm john mal sandon born 16 september 1945 is an australian politician he
was an austr
  alian labor party member of the victorian legislative council from

* Roger Price (Australian politician)   0.96717
  leo roger spurway price born 26 november 1945 is a former australian

```
politician he was ele
  cted as a member of the australian house of representatives

* Maureen Lyster                                          0.96734
  maureen anne lyster born 10 september 1943 is an australian politician she was
an australi
  an labor party member of the victorian legislative assembly from 1985

* Don Bell                                                0.96739
  donald h bell born march 10 1942 in new westminster british columbia is a
canadian politic
  ian he is currently serving as a councillor for the
==========================================================
```

Clusters 0, 1, and 5 appear to be still mixed, but others are quite consistent in content. * Cluster 0: artists, book, him/his * Cluster 1: film, theatre, films, tv, actor * Cluster 2: baseball players * Cluster 3: elections, ministers * Cluster 4: music, orchestra, symphony * Cluster 5: female figures from various fields * Cluster 6: composers, songwriters, singers, music producers * Cluster 7: law, courts, justice * Cluster 8: football * Cluster 9: academia

Clusters are now more pure, but some are qualitatively "bigger" than others. For instance, the category of scholars is more general than the category of baseball players. Increasing the number of clusters may split larger clusters. Another way to look at the size of the clusters is to count the number of articles in each cluster.

[45]:
```python
cluster_count = np.bincount(cluster_assignment[10]())
print(cluster_count)

cluster_dict = {'Cluster 0' : cluster_count[0], 'Cluster 4' : cluster_count[3],
                'Cluster 5' : cluster_count[4], 'Cluster 7' : cluster_count[6],
                'Cluster 9' : cluster_count[8]}

greatest_articles = max(cluster_dict)
least_articles = min(cluster_dict)

print('\n\n' + str(cluster_dict))
print('\n' + greatest_articles + ' contains the greatest number of articles')
print('\n' + least_articles + ' contains the least number of articles')
```

```
[17602  3415  3535  1736  6445  2552  7106  7155   599  8926]


{'Cluster 0': 17602, 'Cluster 4': 1736, 'Cluster 5': 6445, 'Cluster 7': 7106,
'Cluster 9': 599}

Cluster 9 contains the greatest number of articles

Cluster 0 contains the least number of articles
```

Note : Cluster 9 of the 10 clusters above contains the greatest number of articles

Note : Cluster 0 of the 10 clusters above contains the least number of articles

There appears to be at least some connection between the topical consistency of a cluster and the number of its member data points.

Let us visualize the case for K=25. For the sake of brevity, we do not print the content of documents. It turns out that the top words with highest TF-IDF weights in each cluster are representative of the cluster.

[46]:
```
visualize_document_clusters(wiki, tf_idf, centroids[25](),␣
↪cluster_assignment[25](), 25,
                            map_index_to_word, display_content=False) # turn␣
↪off text for brevity
```

```
==========================================================
Cluster 0
blitzattack:0.077
addie:0.048
recordingstheir:0.046
buntingfrom:0.038
hettingers:0.038

==========================================================
Cluster 1
preposition:0.054
2210:0.033
hundreaarsvisningen:0.032
efovi:0.031
allenshortly:0.029

==========================================================
Cluster 2
ibnez:0.216
jeffnominated:0.134
usyd:0.065
sibinki:0.052
19771992according:0.047

==========================================================
Cluster 3
zahida:0.065
pricepottenger:0.042
newsweekkhan:0.031
trag:0.027
slowburn:0.023

==========================================================
Cluster 4
incertidumbre:0.025
```

```
2012frostad:0.023
hareher:0.022
dumbblonde:0.022
disbandedkirwan:0.020

==========================================================
Cluster 5
lopilato:0.160
madeamhali:0.056
1200in:0.044
zahida:0.043
pricepottenger:0.042

==========================================================
Cluster 6
efovi:0.044
2210:0.037
rezas:0.035
wone:0.034
chandanapally:0.031

==========================================================
Cluster 7
pricepottenger:0.066
cranberries:0.058
movessince:0.051
zahida:0.045
popclub:0.043

==========================================================
Cluster 8
madeley:0.095
dilber:0.056
qafl:0.054
tray:0.052
arvo:0.051

==========================================================
Cluster 9
hilger:0.146
repertoryborn:0.096
1982read:0.053
postmodernismlike:0.048
preposition:0.043

==========================================================
Cluster 10
agency:0.075
```

substantialhe:0.050
cowardhis:0.048
deanshobbs:0.048
serieslong:0.048

==

Cluster 11
serieslong:0.144
bostonas:0.092
fons:0.016
interlingual:0.015
2001pasithee:0.012

==

Cluster 12
gan:0.011
turhapuro:0.009
bruschi:0.009
jonsey:0.009
ipfw:0.009

==

Cluster 13
qc:0.109
19771992according:0.104
aulas:0.052
guitarscordray:0.047
sibinki:0.045

==

Cluster 14
scientistagreed:0.144
editionsbrooklyn:0.076
traitors:0.056
ridgeway:0.033
libretti:0.031

==

Cluster 15
anchoragearea:0.125
hyperfine:0.060
arrestkurdnasab:0.051
sibinki:0.049
ngandu:0.045

==

Cluster 16
33story:0.097

conceptevenement:0.061
adipoq:0.033
pearsall:0.029
burkewhite:0.028

==
Cluster 17
19771992according:0.052
famekarl:0.044
5153:0.043
legislaturewhen:0.042
sibinki:0.042

==
Cluster 18
nikoden:0.055
crass:0.045
psihomodo:0.042
posteaster:0.039
19871990principal:0.035

==
Cluster 19
allmvfc:0.095
denn:0.038
addin:0.035
adhunik:0.029
2001pasithee:0.028

==
Cluster 20
conder:0.064
nanri:0.049
33story:0.037
1975one:0.033
daejin:0.025

==
Cluster 21
keimyung:0.075
rolon:0.066
1988director:0.048
lectrices:0.047
15round:0.045

==
Cluster 22
burkewhite:0.146

```
panis:0.116
pramukh:0.106
ftlavallee:0.077
33story:0.064

==========================================================
Cluster 23
eros1988:0.120
ssls:0.105
frazzi:0.065
finglas:0.042
sibinki:0.040

==========================================================
Cluster 24
ebe:0.256
tigerish:0.213
abraha:0.142
playedshe:0.073
coverriley:0.062

==========================================================
```

Looking at the representative examples and top words, we classify each cluster as follows.

- Cluster 0: Literature
- Cluster 1: Film and theater
- Cluster 2: Law
- Cluster 3: Politics
- Cluster 4: Classical music
- Cluster 5: Popular music
- Cluster 6: Jazz music
- Cluster 7: Business and economics
- Cluster 8: (mixed; no clear theme)
- Cluster 9: Academia and research
- Cluster 10: International affairs
- Cluster 11: Baseball
- Cluster 12: Art
- Cluster 13: Military
- Cluster 14: Politics
- Cluster 15: Radio and TV
- Cluster 16: Catholic church
- Cluster 17: Opera and ballet
- Cluster 18: Orchestra music
- Cluster 19: Females from various fields
- Cluster 20: Car racing
- Cluster 21: General sports
- Cluster 22: Rugby
- Cluster 23: Rock music

- Cluster 24: Team sports

Indeed, increasing K achieved the desired effect of breaking up large clusters. Depending on the application, this may or may not be preferable to the K=10 analysis.

Let's take it to the extreme and set K=100. We have a suspicion that this value is too large. Let us look at the top words from each cluster:

[47]:
```python
k=100
visualize_document_clusters(wiki, tf_idf, centroids[k](),␣
↪cluster_assignment[k](), k,
                            map_index_to_word, display_content=False)
# turn off text for brevity -- turn it on if you are curious ;)

print('\n\n')
num_of_clusters = np.sum(np.bincount(cluster_assignment[100]()) < 236)
print(num_of_clusters, 'clusters contain the fewer than 236 articles')
```

```
==========================================================
Cluster 0
isolates:0.137
zincavage:0.082
asiabased:0.056
pantherslabowitch:0.053
machairitsas:0.050

==========================================================
Cluster 1
keimyung:0.170
razed:0.085
pozsgay:0.083
lectrices:0.072
1065ray:0.058

==========================================================
Cluster 2
proa:0.247
examinationspaulker:0.069
10093:0.056
terribles:0.031
berr:0.029

==========================================================
Cluster 3
queer:0.181
yearhansen:0.121
rostersleeth:0.042
awardspreviously:0.036
psihomodo:0.034
```

```
==========================================================
Cluster 4
huld:0.309
1999derek:0.220
stagelavin:0.066
kartvelology:0.041
affiliatechoi:0.031

==========================================================
Cluster 5
franquin:0.192
turhapuro:0.127
wayak:0.054
bruschi:0.046
ebu:0.042

==========================================================
Cluster 6
hettingers:0.059
addie:0.053
eba:0.051
lohiau:0.049
damepazan:0.044

==========================================================
Cluster 7
verwaltung:0.105
childrenseveral:0.099
movessince:0.071
pricepottenger:0.067
barns:0.061

==========================================================
Cluster 8
hilger:0.065
efovi:0.048
preposition:0.045
2210:0.043
repertoryborn:0.043

==========================================================
Cluster 9
raben:0.086
greno:0.076
prospectsaustin:0.061
qasr:0.053
foreignnational:0.040
```

```
============================================================
Cluster 10
serieslong:0.188
bostonas:0.052
studentsresearchthroughout:0.026
panim:0.020
adoption:0.019

============================================================
Cluster 11
calgaryfrom:0.246
eventhe:0.097
dausgaard:0.081
substantialhe:0.073
agency:0.068

============================================================
Cluster 12
fmseaway:0.086
jamali:0.085
appropriated:0.057
magut:0.038
scientistagreed:0.025

============================================================
Cluster 13
buntingfrom:0.098
leivisk:0.051
addie:0.044
pricepottenger:0.043
hettingers:0.043

============================================================
Cluster 14
burkewhite:0.227
pramukh:0.177
mohs:0.084
33story:0.080
ftlavallee:0.057

============================================================
Cluster 15
rolon:0.375
1988director:0.242
15round:0.106
danilovas:0.094
classifieds:0.080
```

==
Cluster 16
qc:0.098
19771992according:0.097
quakes:0.083
200720083:0.083
postfollowing:0.075

==
Cluster 17
lectrices:0.114
catamarcaeduardo:0.072
guji:0.066
conservatorycurran:0.047
styron:0.037

==
Cluster 18
daejin:0.071
thequarter:0.043
33story:0.041
conder:0.030
foundationweiner:0.025

==
Cluster 19
eros1988:0.165
frazzi:0.113
creditcredit:0.067
sibinki:0.044
hsxs:0.044

==
Cluster 20
scientistagreed:0.209
editionsbrooklyn:0.186
traitors:0.082
libretti:0.046
tarkunde:0.044

==
Cluster 21
nikoden:0.213
bradanini:0.083
businesscaan:0.069
macnamee:0.044
rajshahi:0.040

```
==========================================================
Cluster 22
secondgrade:0.215
lemanna:0.045
33story:0.045
ugandaat:0.037
saazish:0.028

==========================================================
Cluster 23
crass:0.127
posteaster:0.045
schwab:0.044
psihomodo:0.039
19871990principal:0.030

==========================================================
Cluster 24
conceptevenement:0.205
33story:0.048
nanri:0.034
forbesfrom:0.025
sslc:0.023

==========================================================
Cluster 25
drigh:0.211
charlottethe:0.097
1375:0.091
phdfrom:0.039
serieslong:0.023

==========================================================
Cluster 26
sotelo:0.259
belgorod:0.178
gerenin:0.058
pasaporte:0.033
tollin:0.027

==========================================================
Cluster 27
ebe:0.261
tigerish:0.220
abraha:0.140
playedshe:0.073
coverriley:0.063
```

```
============================================================
Cluster 28
hyperfine:0.177
anchoragearea:0.128
childrenseveral:0.092
cagnessurmer:0.064
sibinki:0.062

============================================================
Cluster 29
tormentorsafter:0.263
mccord:0.107
laurentides:0.095
serieslong:0.066
usyd:0.060

============================================================
Cluster 30
zahida:0.073
pricepottenger:0.035
newsweekkhan:0.029
upins:0.022
trag:0.021

============================================================
Cluster 31
famekarl:0.198
legislaturewhen:0.049
matrixs:0.046
ngandu:0.045
acrrm:0.040

============================================================
Cluster 32
psihomodo:0.039
wons:0.029
posteaster:0.026
shepps:0.021
chearavanont:0.017

============================================================
Cluster 33
adipoq:0.150
33story:0.071
burkewhite:0.056
dccatanoso:0.053
forbesfrom:0.051
```

==
Cluster 34
lachinelacsaintlouis:0.299
ashok:0.163
iow:0.092
qafl:0.079
ceoexecutive:0.078

==
Cluster 35
panis:0.269
serieslong:0.067
mendras:0.041
morimondo:0.040
bolochoweckyjs:0.036

==
Cluster 36
turhapuro:0.080
bruschi:0.069
usariem:0.038
agencyby:0.030
2001pasithee:0.028

==
Cluster 37
33story:0.131
kirton:0.038
pearsall:0.037
burkewhite:0.026
festivalsns:0.023

==
Cluster 38
7thcentury:0.099
nanri:0.092
conder:0.040
multilevel:0.039
praestholm:0.034

==
Cluster 39
balzar:0.306
golburn:0.034
bostonas:0.021
serieslong:0.020
agencyby:0.012

```
=========================================================
Cluster 40
compositionsher:0.086
krsone:0.072
preposition:0.045
hundreaarsvisningen:0.044
risinger:0.042

=========================================================
Cluster 41
lopilato:0.164
madeamhali:0.068
1200in:0.043
zahida:0.039
refusals:0.038

=========================================================
Cluster 42
preposition:0.062
2210:0.035
efovi:0.034
hundreaarsvisningen:0.031
tenderest:0.030

=========================================================
Cluster 43
ebu:0.127
bks:0.062
norvig:0.059
serieslong:0.045
blukuele:0.045

=========================================================
Cluster 44
19771992according:0.088
superpremium:0.060
sibinki:0.060
5153:0.059
anchoragearea:0.055

=========================================================
Cluster 45
anchoragearea:0.046
legislaturewhen:0.044
5153:0.042
gonino:0.041
19771992according:0.033
```

==
Cluster 46
anchoragearea:0.108
boardthough:0.099
childrenseveral:0.068
armugum:0.067
1991judge:0.064

==
Cluster 47
mtvbase:0.166
abarenb:0.119
cochampions:0.058
cderoy:0.038
erbo:0.037

==
Cluster 48
chandanapally:0.227
acharnians:0.045
efovi:0.044
2210:0.041
bermejoi:0.041

==
Cluster 49
allenshortly:0.121
saqueboutiers:0.072
pitchedin:0.060
sandiegocomborn:0.053
2210:0.043

==
Cluster 50
themamong:0.070
chaplin:0.060
geal:0.054
hareher:0.035
nebrada:0.034

==
Cluster 51
spotthrough:0.143
mcgowans:0.136
casting:0.095
moscowmontpellier:0.086
sdm:0.064

==
Cluster 52
19871990principal:0.138
gaijin:0.069
bakiyevsydykova:0.054
beginningsa:0.048
kobudo:0.043

==
Cluster 53
arvo:0.477
ripp:0.121
karategreeley:0.091
mwandido:0.078
pintail:0.072

==
Cluster 54
toromal:0.122
agreementa:0.068
2008voltaggio:0.053
weitemeyer:0.049
651964:0.028

==
Cluster 55
kabalikat:0.282
nonviolence:0.183
saprang:0.094
campielloin:0.046
lizarazoalfonso:0.027

==
Cluster 56
ftlavallee:0.207
burkewhite:0.136
ungol:0.087
33story:0.080
pramukh:0.073

==
Cluster 57
sderbergborn:0.035
councilwhite:0.027
placesspinning:0.026
recordingstheir:0.025
editorialhe:0.023

==
Cluster 58
brasher:0.234
nanri:0.047
33story:0.039
conder:0.037
secondgrade:0.035

==
Cluster 59
theologians:0.093
mclelland:0.052
seljuks:0.051
33story:0.048
conder:0.037

==
Cluster 60
asiabased:0.127
mendras:0.059
propon:0.035
tahourdin:0.026
late2011:0.025

==
Cluster 61
buytendijk:0.193
antzen:0.132
seiryo:0.052
2010shaw:0.038
etcslapdee:0.032

==
Cluster 62
kenn:0.362
scriptons:0.109
championthree:0.084
serieslong:0.057
straka:0.044

==
Cluster 63
ibnez:0.220
jeffnominated:0.138
usyd:0.067
sibinki:0.053
19771992according:0.048

==
Cluster 64
blitzattack:0.148
recordingstheir:0.093
datebook:0.071
addie:0.051
actressrealizing:0.043

==
Cluster 65
ssls:0.205
finglas:0.086
eros1988:0.059
keyboardsynthesiser:0.052
anchoragearea:0.046

==
Cluster 66
perekop:0.278
useem:0.168
highestselling:0.100
1997best:0.055
kinross:0.031

==
Cluster 67
conder:0.088
1975one:0.044
33story:0.040
gamesjohnson:0.033
ironmanlength:0.027

==
Cluster 68
serieslong:0.158
bostonas:0.152
33story:0.020
conder:0.016
foundationweiner:0.013

==
Cluster 69
denn:0.194
adhunik:0.034
jspvit:0.031
brance:0.029
meadowhall:0.027

==
Cluster 70
deni:0.099
sharewarejunkiescom:0.089
uttam:0.086
preposition:0.039
patras:0.039

==
Cluster 71
sammelans:0.145
trag:0.115
zahida:0.053
slowburn:0.049
lohiau:0.048

==
Cluster 72
cowardhis:0.459
evidencein:0.087
serieslong:0.082
senghors:0.063
agency:0.062

==
Cluster 73
serieslong:0.147
bostonas:0.105
interlingual:0.098
allmvfc:0.063
namadi:0.054

==
Cluster 74
serieslong:0.101
bostonas:0.065
studentsresearchthroughout:0.012
bruschi:0.010
2001pasithee:0.009

==
Cluster 75
2009genuinely:0.196
lectrices:0.177
probodybuilding:0.099
ostende:0.074
hospitaljane:0.073

==
Cluster 76
leaguesanctioned:0.242
litagaylord:0.064
kampi:0.061
lopilato:0.059
outfielderdavanon:0.051

==
Cluster 77
allmvfc:0.233
2004urem:0.085
addin:0.048
alakiti:0.048
184:0.045

==
Cluster 78
neurofibromatosiskorf:0.288
universityuceda:0.268
foundationslomax:0.068
architektur:0.037
writesthis:0.035

==
Cluster 79
barabati:0.296
19771992according:0.072
fireas:0.065
gonino:0.053
sibinki:0.052

==
Cluster 80
gan:0.011
jonsey:0.009
ipfw:0.009
addaction:0.008
fuine:0.007

==
Cluster 81
timesoverland:0.092
trac:0.072
pricepottenger:0.072
19841985after:0.066
luthi:0.054

==
Cluster 82
modellinghe:0.048
13millionsquarefoot:0.047
meadowhall:0.043
2001pasithee:0.038
namadi:0.037

==
Cluster 83
madeley:0.128
dilber:0.080
tray:0.066
jonesa:0.061
triforc3:0.055

==
Cluster 84
pricepottenger:0.096
cranberries:0.086
movessince:0.071
zahida:0.067
cleantech:0.060

==
Cluster 85
dumbblonde:0.038
respuestas:0.031
hareher:0.027
radiowhen:0.025
publishermusic:0.023

==
Cluster 86
countybefore:0.414
good:0.085
caulfieldchristou:0.066
qafl:0.064
unionsshe:0.059

==
Cluster 87
shinners:0.077
topixcom:0.068
19911995he:0.057
alsocodirector:0.048
playedshe:0.047

==
Cluster 88
2012frostad:0.038
reapersince:0.028
incertidumbre:0.028
efovi:0.026
convery:0.022

==
Cluster 89
optometry:0.061
gehen:0.054
schilderijen:0.047
buntingfrom:0.037
kardinal:0.037

==
Cluster 90
anchoragearea:0.120
arrestkurdnasab:0.106
katan:0.081
fantastique:0.052
goromonzi:0.041

==
Cluster 91
qc:0.117
19771992according:0.108
empirein:0.061
aulas:0.052
artus:0.044

==
Cluster 92
conder:0.115
bostonas:0.073
childrenredirect:0.066
kidneyas:0.064
fraternitycoleman:0.064

==
Cluster 93
allmvfc:0.087
addin:0.050
adhunik:0.029
2001pasithee:0.024
meadowhall:0.022

```
==========================================================
Cluster 94
agency:0.106
deanshobbs:0.086
serieslong:0.059
marston:0.059
2008jennings:0.054

==========================================================
Cluster 95
scientistagreed:0.109
traitors:0.040
ridgeway:0.036
yongsan:0.032
awardsloa:0.032

==========================================================
Cluster 96
nanri:0.120
conder:0.040
massing:0.035
watsonnelson:0.031
praestholm:0.030

==========================================================
Cluster 97
fons:0.361
niin:0.209
cineyouth:0.127
serieslong:0.110
imprivata:0.063

==========================================================
Cluster 98
laoghairerathdown:0.155
managerband:0.120
marston:0.119
bolotin:0.090
kiddywinks:0.075

==========================================================
Cluster 99
panik:0.081
danilovas:0.080
15round:0.076
cobeys:0.076
infectionrelated:0.058
```

```
==========================================================


29 clusters contain the fewer than 236 articles
```

The class of team sports has been broken into several clusters, soccer (association football) (11, 22, 24), rugby (76), hockey (80), basketball (86), cricket (87), and American football (85).

The class of baseball has been broken into San Francisco Giants (45), baseball (61, 74), and baseball stats (88).

The class of car racing has been broken into Nascar (20) and Formula 1 (52).

A high value of K encourages pure clusters, but we cannot keep increasing K. For large enough K, related documents end up going to different clusters.

That said, the result for K=100 is not entirely bad. After all, it gives us separate clusters for such categories as Brazil, wrestling, computer science and the Mormon Church. If we set K somewhere between 25 and 100, we should be able to avoid breaking up clusters while discovering new ones.

Also, we should ask ourselves how much **granularity** we want in our clustering. If we wanted a rough sketch of Wikipedia, we don't want too detailed clusters. On the other hand, having many clusters can be valuable when we are zooming into a certain part of Wikipedia.

There is no golden rule for choosing K. It all depends on the particular application and domain we are in.

Another heuristic people use that does not rely on so much visualization, which can be hard in many applications (including here!) is as follows. Track heterogeneity versus K and look for the "elbow" of the curve where the heterogeneity decrease rapidly before this value of K, but then only gradually for larger values of K. This naturally trades off between trying to minimize heterogeneity, but reduce model complexity. In the heterogeneity versus K plot made above, we did not yet really see a flattening out of the heterogeneity, which might indicate that indeed K=100 is "reasonable" and we only see real overfitting for larger values of K (which are even harder to visualize using the methods we attempted above.)

Note : Another sign of too large K is having lots of small clusters. Looking at the distribution of cluster sizes (by number of member data points). 29 of the 100 clusters have fewer than 236 articles, i.e. 0.4% of the dataset