CMSC 476/676 Information Retrieval Homework 5 REPORT JA52979 Sai Teja Challa

Steps to run the program:

In the IDE terminal, You can run the program described below: python3 cluster.py.

Here, 'cluster.py' is the main python program. You must have all libraries installed and your current working directory containing python files in order to run the method described above.

Detailed summary of the code:

In this phase, we need to find the similarity matrix of the entire corpus and perform agglomerative clustering. Here, we are not taking any input directory paths from the user. So, I used the output files from phase-2 i.e,. term weights of each document and included the path of those files in the code to make document vectors.

So, to make document vectors for each document data, I created a function 'load_document_vectors', which iterates over all the output files of phase-2. For each file, it initializes a dictionary where the keys are terms and the values are their corresponding TF-IDF weights. The function parses out the TF-IDF value and stores it in the dictionary. The function returns a dictionary where each key is a document ID and the value is another dictionary (the document vector). Thus, using these document vectors cosine similarity is calculated and a similarity matrix is built.

Here, a similarity matrix is built using the 'build_similarity_matrix' function. This function initializes a square matrix of size equal to the number of documents, with zeros, and later fills the matrix by computing the cosine similarity between each pair of document vectors using the 'cosine_similarity function'. Then it returns the similarity matrix along with a list of document IDs corresponding to the indices in the matrix. Also, the function 'cosine_similarity function' takes two document vectors as input, and identifies the intersection of terms between the two documents. Then calculates the dot product of the vectors for the intersecting terms and the norm (Euclidean length) of each vector. Thus, the dot product is divided by the product of the norms, resulting in 1 indicates an identical direction, while 0 indicates orthogonality (no similarity).

Now, using the similarity matrix, I performed the hierarchical clustering using the 'hierarchical_clustering' function. Here, in the function each document is initially treated as a singleton cluster. This is represented by a dictionary where each key is an index and the value is a list containing the document ID corresponding to that index. A set named 'active_indices' is maintained to keep track of clusters that are still active (i.e., have not been merged into another cluster). The function repeatedly finds the two closest clusters and merges them until only one cluster remains or until no pair of clusters has a similarity above a predefined threshold (e.g., 0.4). It iterates over all active clusters to find the pair with the highest similarity, by checking the current similarity matrix where each entry (i, j) represents the similarity between clusters i and j.

Once the closest pair is found, the clusters are merged. This involves combining the document lists of the two clusters. The merged cluster retains the index of one of the original clusters, and the other index is removed from 'active_indices'. The document list for the merged cluster is updated to include documents from both original clusters.

After merging, the similarity matrix needs to be updated. The similarities involving the merged cluster are recalculated as the maximum similarity between the merged cluster and all other active clusters. This choice of updating rule depends on the linkage criterion used; in this case, it resembles the complete linkage method where the similarity between two clusters is the maximum of the similarities between any member of one cluster to any member of the other. The row and column in the similarity matrix corresponding to the removed cluster are marked inactive (e.g., set to -1). The process stops when there is only one cluster left or when the highest similarity between any two clusters falls below the threshold, indicating that the remaining clusters are sufficiently dissimilar that further merging would not be meaningful.

Hence, the clustering process is done, the function prints messages indicating which clusters are being merged and their similarity.

```
Merging clusters ['407', '410', '412', '414', '405', '403', '401'] and ['416', '418', '421', '423', '425'] with similarity 0.9942904750523394
Merging clusters ['427'] and ['408'] with similarity 0.9938426853377943
Merging clusters ['301', '328', '335', '235', '233', '311', '310', '287', '247'] and ['266'] with similarity 0.9937099027759921
Merging clusters ['377', '352'] and ['370'] with similarity 0.99386572354622
Merging clusters ['301', '328', '335', '285', '233', '311', '310', '287', '247', '266'] and ['295'] with similarity 0.993282415331862
Merging clusters ['301', '328', '335', '285', '233', '311', '310', '287', '247', '266'] and ['295'] with similarity 0.993282415331862
Merging clusters ['324', '292'] and ['251'] with similarity 0.992565087396642
Merging clusters ['248', '259', '264', '313'] and ['334'] with similarity 0.9925267075680406
Merging clusters ['248', '259', '264', '313'] and ['334'] with similarity 0.9995267075680406
Merging clusters ['487', '410', '412', '414', '405', '403', '401', '416', '418', '421', '423', '425'] and ['398', '429', '431'] with similarity 0.992516801265244
Merging clusters ['367', '336'] and ['355', '347'] with similarity 0.9893752243156984
Merging clusters ['367', '336'] and ['355', '347'] with similarity 0.9893752243156984
Merging clusters ['389'] and ['445'] with similarity 0.98873453108059384
Merging clusters ['389'] and ['445'] with similarity 0.9893874531080286
Merging clusters ['248', '259', '264', '313', '334'] and ['244'] with similarity 0.9888238791690452
Merging clusters ['284', '299', '251'] and ['281'] with similarity 0.9868436067956691
Merging clusters ['389', '445'] and ['447', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '410', '
  Merging clusters ['075'] and ['407', '410', '412', '414', '405', '408', '401', '416', '416', '418', '421', '423', '425', '398', 362

Merging clusters ['389', '445'] and ['394'] with similarity 0.9858676817464495

Merging clusters ['388', '445', '394'] and ['099'] with similarity 0.984512554715659

Merging clusters ['388', '445', '394'] and ['099'] with similarity 0.984326757361919

Merging clusters ['318', '323'] and ['331'] with similarity 0.98252861538021

Merging clusters ['412'] and ['415'] with similarity 0.98274615395231146

Merging clusters ['413'] and ['415'] with similarity 0.9827461539513146

Merging clusters ['400'] and ['399'] with similarity 0.9819928927647859

Merging clusters ['474'] and ['240'] with similarity 0.9819928927647859

Merging clusters ['474'] and ['335'] with similarity 0.9819528927647859

Merging clusters ['638', '397', '150', '427', '408'] and ['387'] with similarity 0.980000320479687337

Merging clusters ['838', '445', '394', '080'] and ['377', '372', '370', '341'] with similarity 0.9796770743960959

Merging clusters ['406'] and ['404'] with similarity 0.9787863562989974

Merging clusters ['260'] and ['360'] and ['367', '336', '355', '370', '341'] with similarity 0.977061673033975

Merging clusters ['373', '366'] and ['360'] with similarity 0.9770624731082755

Merging clusters ['408'] and ['409'] with similarity 0.97829331145777449

Merging clusters ['373', '354', '337'] and ['360'] with similarity 0.9749435429169017

Merging clusters ['438'] and ['440'] with similarity 0.9749435429169017

Merging clusters ['438'] and ['450'] with similarity 0.9749435429169017

Merging clusters ['438'] and ['440'] with similarity 0.97497882531809353

Merging clusters ['438'] and ['450'] with similarity 0.9749935429169017

Merging clusters ['438'] and ['450'] with similarity 0.97499353570669

Merging clusters ['438'] and ['440'] with similarity 0.97499353509014

Merging clusters ['438'] and ['440'] with similarity 0.97498353509014

Merging clusters ['438'] and ['440'] with similarity 0.974983535090
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Merging clusters [976] and [125] with similarity 0.891659213708699
Merging clusters [938], 354] and [337] with similarity 0.8906080132479579
Merging clusters [938], 357], 150, 427, 488] and [1367] with similarity 0.990608079687337
Merging clusters [1466] and [1464] with similarity 0.979514608010773
Merging clusters [1466] and [1464] with similarity 0.979514608010773
Merging clusters [1575], 3667] and [1367], 336, 3555, 347] with similarity 0.9797061673033975
Merging clusters [1575], 3667] and [1367], 336, 3555, 347] with similarity 0.977061673033975
Merging clusters [1575], 3667] and [1367], 336, 3555, 347] with similarity 0.977061673033975
Merging clusters [1575], 3667] and [1567], 336, 3557, 347] with similarity 0.977061673033975
Merging clusters [1575], 3667] and [1567], 3367, 3367, 3367, 3367] and [1576] with similarity 0.977061673033975
Merging clusters [1576] and [1567], 3567, 3567] and [1576] with similarity 0.977061673033975
Merging clusters [1576] and [1567], 3567, 3567] with similarity 0.9745982531897533
Merging clusters [1576] and [1576], 4277, 4887, 3877, 3967] and [1572] with similarity 0.9745982531897533
Merging clusters [1576] and [1576], 4277, 4887, 3877, 3967] and [1576], 4277, 4887, 3877, 3967, 3277, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877, 3877
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Above images show the first 100 lines of output.

Finding most similar and most dissimilar pairs:

Using the 'find_similar_and_dissimilar_pairs' function, the most similar and dissimilar pairs are found; It initializes variables to track the maximum and minimum similarities and their corresponding document pairs, iterates over the upper triangle of the similarity matrix (excluding the diagonal) to identify the pairs with the highest and lowest similarity values and returns the document pairs and their similarities for both the most similar and most dissimilar pairs. The document closest to the corpus centroid is found using the 'find_closest_to_centroid' function. It initializes variables to track the highest similarity and the corresponding document, iterates over all document vectors, computing the cosine similarity to the centroid for each. Hence, the document with the highest similarity to the centroid is considered the closest, using cosine similarity as the metric.

```
Most similar pair: ('301', '267') with similarity 0.9266236292651688

Most dissimilar pair: ('499', '343') with similarity 6.4586555926547995e-09

Document closest to centroid: 279 with similarity 0.7685962078737671

o saitejachalla@Saitejas-MacBook-Air IR %
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So, the most similar and most dissimilar pair of html documents, and the document closest to centroid is depicted above.

Major data structures used:

Here, each document is represented as a vector where each dimension corresponds to a term's TF-IDF weight. This is stored in a dictionary where each key is a document ID, and the value is another dictionary mapping terms to their TF-IDF weights. Clusters are implemented using a dictionary where the key is an index (initially corresponding to document IDs) and the value is a list of document IDs in the cluster. This data structure supports efficient merging of clusters and updating of the similarity matrix. A set 'active_indices' used to keep track of active cluster indices in the similarity matrix. This helps in iterating only over currently active clusters during the merging process.

Complexity:

The computation and updating of the similarity matrix throughout the merging process are the main factors influencing the complexity of the hierarchical agglomerative clustering algorithm. Since cosine similarity must be used to compare each pair of documents, creating the initial similarity matrix for n documents needs O(n^2) operations. Depending on the linkage criterion, each merging operation, which is usually performed n-1 times, includes updating the matrix, which can also be difficult. Because of the repeated matrix updates, this technique has an O(n^3) overall time complexity.