```
Homework 1: Finding Similar Items: Textually Similar Documents
  In [1]: from google.colab import drive
           drive.mount('/content/drive')
           import os
           import sys
           sys.path.append('/content/drive/MyDrive/DM_Labs/dataset')
           import pandas as pd
           import numpy as np
           Mounted at /content/drive
           The aim of the project was to find textually similar documents based on Jaccard similarity using the shingling, minhashing, and locality-sensitive hashing (LSH)
           techniques. We have taken the MeDAL dataset (Medical Dataset for Abbreviation Disambiguation for Natural Language Understanding), that is a large
           medical text dataset curated for abbreviation disambiguation.
  In [2]: dataset = pd.read_csv('/content/drive/MyDrive/DM_Labs/dataset/data.csv', sep='\t', on_bad_lines='skip')
           Visualizing loaded rows out of 1M rows:
  In [4]: dataset
  Out[4]:
                   Unnamed: 0
                                                                            LOCATION
                                                                                                                   LABEL
                               alphabisabolol has a primary antipeptic action...
                                                                                                                  substrate
                                                                                      carcinosarcoma|recovery|reference|recovery|aft...
                1
                                a report is given on the recent discovery of o...
                                                                     24|49|68|113|137|172
                              the virostatic compound nndiethyloxotetradecyl...
                2
                          3 rmi rmi and rmi are newly synthetized nrdibenz...
                3
                                                                        25|82|127|182|222 compounds|compounds|inhibitory|lethal doses|ca...
                               a doubleblind study with intraindividual compa... 22|26|28|77|90|144|158|203 oxazepam|placebo|oral administration|pentagast..
                                                                                24|59
            999995
                      999995 the human gene for producing alcohol dehydroge...
                                                                                                          liver biopsy|complete
            999996
                      999996
                              measurement of CS in saliva has excited intere..
                                                                      2|27|64|74|76|83|118
                                                                                         steroids|active|serum|sensitive|specific|assay...
                                                                                         serum|albumin|antiserum|after|vitro fertilization
                                                                         14|15|37|60|173
            999997
                      999997
                               a timeresolved fluoroimmunoassay trfia for unc...
            999998
                      999998
                               porphyria cutanea tarda pct results from a met...
                                                                              59|64|205
                                                                                                       groups|study|degradation
            999999
                             recent advances in methodology allow the mass ...
                                                                                                              electrophoresis
           1000000 rows × 4 columns
           We take only a slice of the dataset and drop all the columns that are different from TEXT.
  In [5]: small_dataset = dataset[:1000]
           small_dataset = small_dataset['TEXT']
  In [6]: small_dataset[0]
  Out[6]: 'alphabisabolol has a primary antipeptic action depending on dosage which is not caused by an alteration of the phval
           ue the proteolytic activity of pepsin is reduced by percent through addition of bisabolol in the ratio of the antipep
           tic action of bisabolol only occurs in case of direct contact in case of a previous contact with the ATP the inhibiti
           ng effect is lost'
           Shingling
           Let's define a function that constructs k–shingles of a given length (k=5) from a given document, computes a hash value for each unique shingle and
           represents the document in the form of an ordered set of its hashed k-shingles. Defining a shingling function that uses list comprehension, defining a loop
           while iterating the list to make it faster.
  In [7]: def shingles(text, size):
               chars = list(text) # Splitting the text
               return [''.join(chars[i:i+size]) for i in range(len(chars) - size + 1)]
           # Joining with an empty char from the i-th char to the 'i-th + size-1' char, 'len(chars) - size + 1' times
           \mathbf{k} = \mathbf{5} for small documents.
  In [8]: k = 5
           five_shingles = shingles(small_dataset[0], k)
           five_shingles[:10] # Just to show the first 10 5-shingles of the first document
  Out[8]: ['alpha',
             'lphab'
             'phabi',
             'habis'
             'abisa'
             'bisab'
             'isabo',
             'sabol',
             'abolo'
            'bolol']
           crc32 will be used to hash the shingles.
  In [9]: from binascii import crc32
           import time
 In [10]: def shinglify(dataset, k):
               t0 = time.time()
               docs_as_hashed_shingles = {}
               # For each document
               for i in range(len(dataset)):
                    hashed_shingles = set()
                    text = dataset[i]
                    # For each shingle
                    for shingle in set(shingles(text, k)): # Directly converts to a shingle set to avoid repetitions
                        crc_hash = crc32(shingle.encode('utf-8')) & 0xffffffff
                        hashed_shingles.add(crc_hash)
                    docs_as_hashed_shingles[i] = hashed_shingles
               t1 = time.time()
               return docs_as_hashed_shingles, t0, t1
 In [11]: | shingled_dataset, t0, t1 = shinglify(small_dataset, k) # Returns times as well
           print(str(k) + '-Shingling ' + str(len(small_dataset)) + ' docs took: %.2f seconds' %(t1 - t0))
           5-Shingling 1000 docs took: 0.75 seconds
           Compare Sets
           Let's define a method which computes the Jaccard similarity of two sets of integers: two sets of hashed shingles.
In [129]: def jaccard_2docs(doc1: set, doc2: set):
             return len(doc1 & doc2)/len(doc1 | doc2)
In [130]: def similarity_matrix(shingled_dataset):
              t0 = time.time()
             sim_matrix = np.zeros((len(small_dataset),len(small_dataset)))
              for row in range(len(small_dataset)):
               for col in range(row, len(small_dataset)):
                 if(row == col): # Skipping the similarity for the same document as it would be 1
                  sim_matrix[row][col] = jaccard_2docs(shingled_dataset[row], shingled_dataset[col])
             t1 = time.time()
              return sim_matrix, t0, t1
In [132]: sim_matrix, t0, t1 = similarity_matrix(shingled_dataset)
           shingling_sim_time = t1 - t0
           print('double-loop Similarity Matrix computation for ' + str(len(small_dataset)) + ' docs took: %.2f seconds' %shing
           ling_sim_time)
           double-loop Similarity Matrix computation for 1000 docs took: 50.52 seconds
           Saved the time for the first technique.
In [133]: sim_matrix[0][:10]
                             , 0.05121639, 0.06199461, 0.05589226, 0.04317656,
Out[133]: array([0.
                  0.07427938, 0.05474453, 0.05051546, 0.05222734, 0.05682782])
           Let's print the maximum of the similarity matrix and finding which are the documents with the maximum value.
In [134]: print(np.max(sim_matrix))
           print(np.unravel_index(np.argmax(sim_matrix, axis=None), sim_matrix.shape))
           0.4558180227471566
           (173, 175)
           As we can see, the following texts have some parts in common.
In [135]: small_dataset[173]
Out[135]: 'reduced coenzyme qcytochrome c reductase from bovine heart mitochondria complex iii was incorporated into phospholip
           id LDV by the cholate dialysis procedure soybean phospholipids or mixtures of purified phosphatidylcholine phosphatid
           ylethanolamine and cardiolipin could be used oxidation of reduced coenzyme q by the reconstituted vesicles with cytoc
           hrome c as oxidant showed the following energycoupling phenomena protons were translocated outward with a coupling ra
           tio he of measurements with mitochondria under similar conditions showed an he ratio of proton translocation was not
           seen in the presence of uncoupling agents and was in addition to the net acidification of the medium from the overall
           oxidation reaction potassium ions were taken up by the reconstituted vesicles in the presence of valinomycin in a rea
           ction coupled to electron transfer the coupling ratio for k uptake ke was in the vesicles and approximately in mitoch
           ondria the rate of oxidation of reduced coenzyme q by the reconstituted LDV was stimulated up to fold by uncouplers o
           r by valinomycin plus nigericin and k ions addition of valinomycin CT in a k medium caused a transient stimulation of
           electron transfer the results indicate that SE coupling can be observed with isolated reduced coenzyme qcytochrome c
           reductase if the enzyme complex is properly incorporated into a phospholipid vesicle'
In [136]: small_dataset[175]
Out[136]: 'nadhcoenzyme q reductase from bovine heart mitochondria complex i was incorporated into phospholipid LDV by the chol
           ate dialysis procedure mixtures of purified phosphatidylcholine and phosphatidylethanolamine were required oxidation
           of nadh by coenzyme q catalyzed by the reconstituted vesicles was coupled to proton translocation directed inward wit
           h an he ratio greater than similar experiments measuring proton translocation in submitochondrial particles gave an h
           e ratio of the proton translocation in both systems was not seen in the presence of uncoupling agents and was in addi
           tion to the net proton uptake from the reduction of coenzyme q by nadh electron transfer in the reconstituted LDV als
           o caused the uptake of the permeant anion tetraphenylboron the rate of electron transfer by the reconstituted vesicle
           s was stimulated about fold by uncouplers or by valinomycin plus nigericin and k ions the results indicate that energ
           y coupling can be observed with isolated nadhcoenzyme g reductase if the enzyme complex is properly incorporated into
           a phospholipid vesicle'
           Min Hashing
           Let's define a function which builds a minHash signature (in the form of a vector or a set) of a given length n from a given set of integers (a set of hashed
           First of all, we take numHashes independent hash functions.
 In [90]: # number of random hash functions
           num_hashes = 100
           After that, we find the maxShingleID, that will be used lately for the hash function.
 In [92]: t0 = time.time()
           maxShingleID = 0
           for doc_id in shingled_dataset:
             shingle_id_set = shingled_dataset[doc_id]
             signature = []
              for i in range(0, num_hashes):
               for shingle_id in shingle_id_set:
                 if(maxShingleID < shingle_id):</pre>
                    maxShingleID = shingle_id
           t1 = time.time()
           max\_shingle\_time = t1 - t0
 In [93]: print(maxShingleID)
           # We need the next largest prime number after 'maxShingleID'.
           # http://compoasso.free.fr/primelistweb/page/prime/liste_online_en.php
           nextPrime = 4294895617
           4294895493
 In [94]: import random
           random.seed(42)
           def random_coeffs(k):
             # k random vaues
             rand_list = []
              for i in range(k):
               # random shingle ID
               rand_idx = random.randint(0, maxShingleID)
               # uniqueness check
               while rand_idx in rand_list:
                 rand_idx = random.randint(0, maxShingleID)
               rand_list.append(rand_idx)
              return rand_list
           For each hash function, generate a different coefficient a and b.
 In [95]: coeff_A = random_coeffs(num_hashes)
           coeff_B = random_coeffs(num_hashes)
           Checking that they're not representing the same line (like 3x+12 and x+4).
 In [96]: for a, b in zip(coeff_A, coeff_B):
             assert a not in coeff_B
             assert b not in coeff_A
             for x, y in zip(coeff_A, coeff_B):
               if(a != x and b != y):
                 assert a/b != x/y
           For each of the shingles of a document, calculate its hash using i_{th} hash function.
 In [97]: | t0 = time.time()
           # docs as signatures
           signatures = []
           for doc_id in shingled_dataset:
             shingle_id_set = shingled_dataset[doc_id]
              signature = [] # result signature
              for i in range(num_hashes):
               min_hash = nextPrime + 1 # initialize min_hash to be greater than the nextPrime
               for shingle_id in shingle_id_set:
                 hash_code = (coeff_A[i] * shingle_id + coeff_B[i]) % nextPrime # (ax + b) % c
                 if hash_code < min_hash:</pre>
                   min hash = hash code
               signature.append(min_hash) # keep the min_hash
              signatures.append(signature) # keep the entire signature of document doc_id
           t1 = time.time()
           min_hashing_time = t1 - t0
           min_hashing_time
 Out[97]: 32.12442111968994
 In [98]: num_docs = len(shingled_dataset) # 1000
           Time to compare the signatures (task 4):
In [111]: def compare_signatures():
             t0 = time.time()
             matrix = np.zeros((len(shingled_dataset), len(shingled_dataset)))
             for i in range(num_docs):
               doc1_signature = signatures[i]
               # For each of the other test documents...
               for j in range(i, num_docs):
                 if(i == j):
                   continue
                  doc2_signature = signatures[j]
                  count = 0
                  for k in range(num_hashes):
                    agree = 0
                    if(doc1_signature[k] == doc2_signature[k]):
                      agree = 1
                    count = count + agree # on how many do they agree?
                 matrix[i][j] = float(count) / float(num_hashes) # assigning similarity
              t1 = time.time()
              return matrix, (t1 - t0)
           The percentuage matrix will have on the rows and on the columns all the documents.
In [112]: | minHash_sim_matrix, compare_time = compare_signatures()
In [113]: minHash_tot_time = max_shingle_time + min_hashing_time + compare_time
           minHash_tot_time
Out[113]: 46.102508544921875
In [104]: threshold = 0.3
In [114]: | for i in range(num_docs):
             for j in range(i, num_docs):
               if(i == j):
                  continue
               if minHash_sim_matrix[i][j] > threshold:
                 print (minHash_sim_matrix[i][j])
           0.4
           0.32
           0.44
           0.35
           0.31
           0.32
           The documents number 408 and 410 have the highest percentuge of same hash values.
In [115]: print(np.max(minHash_sim_matrix))
           print(np.unravel_index(np.argmax(minHash_sim_matrix, axis=None), minHash_sim_matrix.shape))
           0.44
           (408, 410)
           Let's check values of before:
In [116]: print(minHash_sim_matrix[173, 175]) # still high similarity on these two
           0.4
In [117]: small_dataset[408]
Out[117]: 'the nadpspecific glu dehydrogenase of neurospora crassa was digested with trypsin and peptides accounting for out of
           the residues of the polypeptide chain were isolated and substantially sequenced additional experimental detail has be
           en deposited as supplementary publication sup pages with the british library lending division boston spa wetherby w y
           orkshire ls bq uk from whom copies may be obtained under the terms given in biochem j'
In [118]: small_dataset[410]
Out[118]: 'peptic and chymotryptic peptides were isolated form the nadpspecific glutamate dehydrogenase of neurospora crassa an
           d substantially sequenced out of residues in the polypeptide chain were recovered in the peptic and in the chymotrypt
           ic peptides together with the tryptic peptides wootton j c taylor j g jackson a a chambers g k fincham j r s biochem
           j these establish the CR CS of the chain including the acid and NH assignments except for seven places where overlaps
           are inadequate these remaining alignments are deduced from information on the cnbr fragments obtained in another labo
           ratory blumenthal k m moon k smith e l j biol chem further information has been deposited as supplementary publicatio
           n sup pages with the british library lending division boston spa wetherby w yorkshire ls bq uk from whom copies may b
           e obtained under the terms given in biochem j'
           Same words: boston, biochem, j, ls, bq, uk, dehydrogenase, neurospora, polypeptide, etc...
           LSH
           A class LSH that implements the LSH technique: given a collection of minhash signatures (integer vectors) and a similarity threshold t, the LSH class (using
           banding and hashing) finds candidate pairs of signatures agreeing on at least a fraction t of their components.
           \{{b \atop b} r=n ^{(1/b)^{1/r} \sim s} remember from the slides.
In [205]: bands = 20 # between 1 and the number of hashes 100
           rows_per_band = num_hashes / bands
           lsh_threshold = 1/bands ** (1/float(rows_per_band))
           lsh_threshold
Out[205]: 0.5492802716530589
           Defining a function that given a signature and number of bands, returns a band_hash_list containing the cycled mod_bands buuckets of the hashes of the
           signature.
In [259]: '''
           def band_hash(bands, minHash_signature):
             band_hash_list = []
             band_hash = 0
             for i in range(len(minHash_signature)): # for every hash in the signature
                    if i % bands == 0: # number of bands modular cycle (#bands different classes)
                        if i > 0:
                          band_hash_list.append(band_hash)
                        band_hash = 0
                    band_hash = hash(minHash_signature[i]) # hashing i-th value of the signature
              return band_hash_list
           Defining the LSH function.
In [178]: import itertools
           import time
In [260]: '''
           def LSH(signatures, threshold, bands, num_hashes):
             t0 = time.time()
             final_result = {} # dict: (pair of similar documents) -> similarity (> threshold)
             lsh_signatures = {}
              band_hashes = {}
              doc_id = 0
              for signature in signatures:
               lsh_signatures[doc_id] = signature
               minhash_sig = signature
               new_hashes = band_hash(bands, minhash_sig)
               # Time to construct the dictionary that links signatures and buckets
               for i in range(len(new_hashes)): # for every element of the new hashes
                 if i not in band_hashes: # if not already added
                    band_hashes[i] = {} # create instance in the dictionary
                  if new_hashes[i] not in band_hashes[i]:
                   band_hashes[i][new_hashes[i]] = [] # insert the first element
                    band_hashes[i][new_hashes[i]].append(doc_id)
                    band_hashes[i][new_hashes[i]].append(doc_id)
               doc_id = doc_id + 1
              found_similarities = set()
              # Compare each bucket signatures
              for h in band_hashes:
               for bucket in band_hashes[h]:
                 if len(band_hashes[h][bucket]) > 1: # if at least two elements...
                    for two_docs in itertools.combinations(band_hashes[h][bucket], r=2):
                      if two_docs not in found_similarities:
                        found_similarities.add(two_docs)
                        sim = jaccard_2docs(set(lsh_signatures[two_docs[0]]), set(lsh_signatures[two_docs[1]]))
                        if(float(sim) > lsh_threshold):
                          print(sim)
                          final_result[two_docs] = sim
             t1 = time.time()
             return final_result, (t1 - t0)
           Couldn't get the last part to work, some fixes are needed.
  In [ ]: !jupyter
```

LAB.1