ML PROJECT REPORT: FINDING PERTINENT COURT CASE TO INPUT CASE USING DOCUMENT SIMILARITY

Raghav Bhatnagar(IMT2014042) and Tanya Shrivastava(IMT2014058)

December 3, 2017

Problem Statement

Given a corpus of cases, and a test case, find the most similar case to the test case from the corpus.

Motivation

A lot of time is spent in legal proceedings searching for similar cases. This can help save a lot of time, by automatically filtering relevant cases, and reducing valuable research time spent in searching.

Solution

The code takes a filename and matches the file with an existing corpus to find the most similar files. First the documents in the corpus are parsed, and a dictionary of file:content is formed (filename being the key and content being the value). This dictionary is then passed into the tokenizer function, which parses and converts the text corresponding to each file into a list of tokens. The tokenizer function also removes the stop words, and stems the remaining words to give the final list of words.

This resultant dictionary is passed into the tfidf vectoriser that generates tf/idf values for each (document, word) pair. The tf-idf vectorization of a corpus of text documents assigns each word in a document a number that is proportional to its frequency in the document and inversely proportional to the number of documents in which it occurs. These tf/idf vectors are then parsed into an m^*n (document * words) matrix. Latent Semantic Analyses (LSA) is then applied to this matrix LSA analyses relationships between a set of documents and the terms they contain by producing a set of concepts related to the documents and terms. The m^*n (document*words) matrix is split and expressed as a product of m^*k (documents*topics) x k^*n (topics*words) matrices $K \ll m,n$. SVD (Singular Value Decomposition) is used for dimensionality reduction. From the resultant document*topics matrix, The dot product of the row corresponding to test file is taken with the other rows. Highest dot products reveal the most similar documents.

Listing 1: Python Code:

```
1 from nltk.corpus import stopwords
2 from nltk.tokenize import word_tokenize
3 from nltk.tokenize import RegexpTokenizer
4 from nltk import PorterStemmer
5 import string
6 import os
7 from re import sub
8 from sklearn.feature_extraction.text import TfidfVectorizer
9 from nltk.stem.porter import PorterStemmer
10 from sklearn.decomposition import TruncatedSVD
11 from sklearn.metrics.pairwise import cosine_similarity
12 import scipy
13 import numpy as np
14
15 path = './cases'
16
  token_dict = {}
17
  #function to tokenize, remove stop words and stem the remaining
18
   def tokenize(text):
19
20
       #setting stop words (defining the corpus of stop words)
21
       #Remove non ascii characters
22
       stop_words = set(stopwords.words('english'))
23
24
       #following added to remove dates
25
26
       stop_words.update([u'january', u'february', u'march', u'april', u'may'←
           , u'june', u'july', u'august', u'september', u'october', u'↔
          november', u'december' ])
       stop_words.update([u'monday', u'tuesday', u'wednesday', u'thursday', u←
27
           'friday', u'saturday', u'sunday'])
28
       #setting regexp so that only words taken and punctuation and digits \leftarrow
29
           removed
30
       tokenizer = RegexpTokenizer(r'[a-zA-Z][^\s]*\b')
       word_tokens=tokenizer.tokenize(text) #tokenizing
31
32
       #removing stop words and stemming
33
       final tokens = []
34
       for word in word_tokens:
35
           if (word.lower() not in stop_words):
36
               #remove numberd from words - trail231 becomes trial
37
               word = sub(r' d+', '', word)
38
```

```
final_tokens.append(str(PorterStemmer().stem(word.lower())))
39
        # stripped_text = " ".join(final_tokens)
40
        return final tokens
41
42
43
   def findSimilar(path, filename):
        for dirpath, dirs, files in os.walk(path):
44
45
            #os.walk() generates the file names in a directory tree by walking←
                 the tree
            for f in files:
46
                fname = os.path.join(dirpath, f) #creates filename as path+←
47
                    file
                #print "fname=", fname
48
49
                with open(fname) as pearl:
                     text = pearl.read()
50
                     #remove unwanted utf-8 characters
51
                     text=sub(r'[^\x00-\x7f]|[\x11]',r'',text)
52
                     token dict[f] = text.translate(None, string.punctuation)
53
                     #stored text corresponding to file in dictionary
54
55
56
        #find fileIndex of our target document.
        keys = token_dict.keys()
57
        if filename not in keys:
58
            print "Filename error. File not in corpus"
59
60
            return
        fileIndex = keys.index(filename)
61
62
63
        #taken tokenising function, tokenises the files, and generates the \mathsf{tf}/\!\!\leftarrow
           idf values for each (file,word)
        tfidf = TfidfVectorizer(tokenizer=tokenize)#expects list
64
65
        #Fit the Tf/Idf model, and Transform a document into TfIdf coordinates
66
        tfs = tfidf.fit_transform(token_dict.values())
67
68
        #print tfs
69
        #feature_names = tfidf.get_feature_names()
        #print feature_names
70
        #print tfidf.vocabulary
71
        print "Shape of tfidf matrix = " + str(tfs.shape)
72.
73
74
        #creating a 2D TF/IDF matrix from tfs
75
        tfs_matrix = [[0 \text{ for } x \text{ in range}(tfs.shape[1])] \text{ for } y \text{ in range}(tfs.} \leftarrow
           shape[0])] #initialised to prevent list comprehension
        i = 0
76
       while i < tfs.shape[0]:</pre>
77
            j = 0
78
            while j < tfs.shape[1]:</pre>
79
                tfs_matrix[i][j] = tfs[i,j]
80
                j=j+1
81
```

```
82
            i=i+1
83
        #Sigma comes out as a list rather than a matrix
84
        u,sigma,vt = scipy.linalg.svd(tfs_matrix)
85
86
        #Reconstruct MATRIX
87
88
        reconstructedMatrix= scipy.dot(scipy.dot(u,scipy.linalg.diagsvd(sigma,←
            tfs.shape[0],len(vt))),vt)
        print "Reconstructed Matrix: "
89
        print reconstructedMatrix
90
91
        # Parse the reconstucted matrix and take dot product of each row with
92
        # every row to get similarity of every two documents. Find out the max
93
        # similarity of each document.
94
95
        i = 0
        count = 0
96
        maxSimilarity=0
97
        THETA = np.array(reconstructedMatrix[fileIndex])
98
99
        doc1=-1
        while i < tfs.shape[0]:</pre>
100
            doc2=fileIndex
101
102
            if i != fileIndex:
                #calculating dot product
103
                X = np.array(reconstructedMatrix[i])
104
                 similarity = X.dot(THETA)
105
106
                 if similarity > maxSimilarity:
107
                     maxSimilarity=similarity
108
                     doc1=i
                count = count + 1
109
110
            i=i+1
        print "Similarity of " + keys[doc2] + " is maximum with: "+ keys[doc1]←
111
             + ": " + str(maxSimilarity)
112
113
    filename = raw_input("What is the name of the target file?: ")
114
115
116 findSimilar(path, filename)
```

Output Snippets

The code on running asks the user to input the name of the test file. It then returns the name of the most similar file.

0.1 TF/IDF vectors

TF/IDF vectors look as follows:

```
What is the name of the target file?: 22.txt
  (0, 34)
                 0.152497047038
  (0, 639)
                 0.152497047038
  (0, 562)
                 0.152497047038
  (0, 464)
                 0.0906404514996
  (0, 523)
                 0.100975993391
  (0, 1096)
                 0.0954843894601
  (0, 2)
                 0.214631169748
  (0, 1091)
                 0.152497047038
  (0, 210)
                 0.11481373013
  (0, 372)
                 0.135821913663
  (0, 839)
                 0.152497047038
  (0, 1318)
                 0.152497047038
  (0, 1066)
                 0.152497047038
  (0, 944)
                 0.152497047038
  (0, 1257)
                 0.135821913663
  (0, 155)
                 0.100975993391
  (0, 937)
                 0.135821913663
  (0, 277)
                 0.152497047038
  (0, 1365)
                 0.107315584874
  (0, 1083)
                 0.0906404514996
  (0, 815)
                 0.152497047038
  (0, 1364)
                 0.144939329205
  (0, 1233)
                 0.100975993391
  (0, 776)
                 0.107315584874
  (0, 126)
                 0.11481373013
```

0.2 Vocabulary

Vocabulary shows the index assigned to each word. A snippet of the vocabulary is:

```
'represent': 1019, 'consider': 260, 'lack': 657,
dren': 210, 'whose': 1337, 'accus': 9, 'corps': 271,
                                        'biki': 138,
506, 'neglig': 805, 'introduc': 605,
 702, 'util': 1288, 'candid': 181, 'worst': 1358,
 ': 1162, 'look': 703, 'school': 1064, 'impact': 577,
  'rench': 1011, 'bill': 139, 'miscarriag': 763, 'secor
ven': 395, 'hide': 544, 'wreck': 1360, 'section': 1075
                                        'told': 1241, 'or
807, 'ever': 397, 'onethousand': 843,
men': 747, 'lodg': 698, 'privat': 937, 'drew': 356,
       'search': 1069, 'daughter': 301,
                                          'bremner': 159
udi': 1172, 'narrow': 796, 'controversi': 266, 'joshua
  'total': 1245, 'establish': 393, 'describ': 323, 'wou
ster': 463, 'call': 175, 'taken': 1200, 'furor': 480,
warn': 1319, 'glass': 497, 'connecticut': 255, 'particu
n': 1247, 'none': 820, 'word': 1352, 'room': 1043, 'hou
    'ms': 787, 'learn': 670,
                              'dec': 308, 'tiahleigh':
': 578, 'intercours': 600, 'minimum': 760, 'british':
    25, 'polic': 912, 'anoth': 59, 'travel': 1251,
'organis': 853, 'negoti': 806, 'simpl': 1112,
                            'attempt': 85,
nstr': 319, 'short': 1101,
                     'greed': 514,
                                    'help': 542.
       order': 851.
```

0.3 SVD Reconstructed Matrix and Final Output

The matrix reconstructed by SVD (the document*topics matrix) and the final output look as follows:

```
tanya@tanya-Inspiron-5537:~/smartcity/360.legal$ python training.py
What is the name of the target file?: 23.txt
Shape of tfidf matrix = (29, 1373)
Reconstructed Matrix:
   3.48028897e-17
                    9.92722614e-18
                                     2.14631170e-01 ...,
                                                         2.25514052e-17
   6.56890991e-17
                  -1.07708710e-17]
                                     9.54097912e-18 ..., -7.19910243e-17
  -1.43982049e-16 -1.62155987e-17
                   1.20956305e-17]
    1.45364406e-16
                  -9.10052199e-18
                                     5.63785130e-17 ..., -1.26309553e-17
 [ -4.03865309e-17
   8.94466792e-18 3.06761452e-17]
  -4.27175656e-17 -7.26550981e-17
                                    -3.51281504e-17 ..., -3.42607887e-17
    3.49047585e-01 -8.49201352e-17]
                  3.42065785e-17 -2.14672030e-17 ..., -5.59448321e-17
  -2.38524478e-17
                  -5.20417043e-18]
    5.74627151e-17
  -1.16009632e-16 -2.81621514e-17 -2.42861287e-17 ..., 3.99251780e-02
    2.64653750e-16 -6.28159634e-17]]
Similarity of 23.txt is maximum with: 22.txt: 0.111255865743
```

Accuracy

The code was run on a smaller corpus of 29 files to check for accuracy. Accuracy was manually calculated.

• The files with highest similarity were actually similar cases: 21

• Files with highest similarity were somewhat similar: 4

• Files with highest similarity were not similar: 4

Accuracy: 72.4 %

Python Libraries Used

• os: To traverse and read files

• nltk: To tokenize, remove stop words, and for stemming

• sklearn.TfidfVectorizer : To create tf/idf vectors

• scipy.linalg : For SVD

• numpy : For dot products

References

The corpus of files were taken from:

1. https://www.scoopwhoop.com/inothernews/indian-court-cases/.p2xi3qstb

2. http://abcnews.go.com/US/interesting-legal-cases-2011/story?id=152536661

 $3. \ https://www.criminal-lawyers.com.au/criminal-law/case-studies/robbery-offences$

5. http://www.news.com.au/national/crime/australias-worst-crimes-in-2015/news-story/17777baae928809al

 $6. \ http://www.complex.com/sports/2014/05/the-50-most-infamous-criminals-in-sports-history/sam-hurd$

7. https://indiankanoon.org/docfragment/92453/?formInput=cases

8. https://www.austlii.edu.au