# labassignment7

August 2, 2024

# 1 Lab Assignment 7: Database Queries

### 1.1 DS 6001: Practice and Application of Data Science

#### 1.1.1 Instructions

Please answer the following questions as completely as possible using text, code, and the results of code as needed. Format your answers in a Jupyter notebook. To receive full credit, make sure you address every part of the problem, and make sure your document is formatted in a clean and professional way.

#### 1.1.2 Problem 0

Import the following libraries, load the .env file where you store your passwords (see the notebook for module 4 for details), and turn off the error tracebacks to make errors easier to read:

```
[]: import numpy as np
     import pandas as pd
     import sys
     import os
     import requests
     import psycopg2
     import pymongo
     import json
     from bson.json_util import dumps, loads
     from sqlalchemy import create_engine
     import dotenv
     from pymongo import MongoClient
     # change to the directory where your .env file is
     os.chdir(r"C:\Users\qaism\OneDrive - University of_
      →Virginia\Documents\GitHub\MSDS\ds6001databases")
     dotenv.load dotenv() # register the .env file where passwords are stored
     sys.tracebacklimit = 0 # turn off the error tracebacks
```

#### 1.1.3 Problem 1

For this problem, we will be building a PostgreSQL database that contains the collected works of Shakespeare.

collected The data bv Catherine Devlin from were the repository at https://opensourceshakespeare.org/. The database will have four tables, one representing works by Shakespeare, one for characters that appear in Shakespeare's plays, one for chapters (this is, scenes within acts), and one for paragraphs (that is, lines of dialogue). The data to populate these four tables are here:

In PostgreSQL, it is best practice to convert all column names to lower-case, as case sensitive column names will require extraneous double-quotes in any query. We first convert the column names in all four dataframe to lowercase:

```
[]: works.columns = works.columns.str.lower()
    characters.columns = characters.columns.str.lower()
    chapters.columns = chapters.columns.str.lower()
    paragraphs.columns = paragraphs.columns.str.lower()
```

You will build a database and populate it with these data. The ER diagram for the database is:

There's no codebook, unfortunately, but the values in the columns are mostly self-explanatory:

```
[]:
     works.head()
[]:
              workid
                                            title
                                                                           longtitle
                                                    Twelfth Night, Or What You Will
     0
             12night
                                    Twelfth Night
     1
            allswell
                       All's Well That Ends Well
                                                          All's Well That Ends Well
     2
          antonycleo
                            Antony and Cleopatra
                                                               Antony and Cleopatra
         asyoulikeit
                                   As You Like It
                                                                      As You Like It
                                                               The Comedy of Errors
        comedyerrors
                                 Comedy of Errors
        date genretype
                         notes
                                    source
                                            totalwords
                                                         totalparagraphs
     0
       1599
                      С
                           NaN
                                                 19837
                                                                     1031
                                      Moby
     1 1602
                           NaN
                                                                     1025
                      С
                                      Moby
                                                 22997
     2 1606
                      t
                           NaN
                                      Moby
                                                 24905
                                                                     1344
     3 1599
                                                                      872
                      С
                           NaN
                                Gutenberg
                                                 21690
     4 1589
                      С
                           NaN
                                      Moby
                                                 14692
                                                                      661
```

```
[]: characters.head()
```

```
[]:
                 charid
                                   charname
                                                         abbrev
                                                                       works \
                                              First Apparition
     0
        1apparition-mac
                          First Apparition
                                                                     macbeth
     1
               1citizen
                              First Citizen
                                                 First Citizen
                                                                 romeojuliet
     2
           1conspirator First Conspirator First Conspirator
                                                                  coriolanus
                           First Gentleman
                                               First Gentleman
     3
         1gentleman-oth
                                                                     othello
     4
                  1goth
                                 First Goth
                                                     First Goth
                                                                       titus
       description speechcount
               NaN
                             1.0
     0
                             3.0
     1
               NaN
     2
               NaN
                             3.0
     3
               NaN
                             1.0
     4
               NaN
                             4.0
[]: chapters.head()
[]:
         workid
                chapterid
                            section
                                      chapter
                                                          description
      12night
                   18704.0
                                 1.0
                                          1.0
                                               DUKE ORSINO's palace.
                   18705.0
                                 1.0
                                          2.0
     1 12night
                                                       The sea-coast.
     2 12night
                   18706.0
                                 1.0
                                          3.0
                                                      OLIVIA'S house.
     3 12night
                   18707.0
                                 1.0
                                          4.0
                                               DUKE ORSINO's palace.
     4 12night
                   18708.0
                                 1.0
                                          5.0
                                                      OLIVIA'S house.
[]: paragraphs.head()
[]:
         workid paragraphid paragraphnum
                                           charid \
     0 12night
                     630863
                                        3
                                              xxx
     1 12night
                     630864
                                           ORSINO
     2 12night
                                       19
                                            CURIO
                     630865
     3 12night
                     630866
                                       20
                                           ORSINO
     4 12night
                     630867
                                       21
                                            CURIO
                                                 plaintext \
       [Enter DUKE ORSINO, CURIO, and other Lords; Mu...
        If music be the food of love, play on; \n[p]Giv...
     1
     2
                              Will you go hunt, my lord?\n
     3
                                            What, Curio?\n
                                               The hart.\n
     4
                                              phonetictext
               ENTR TK ORSN KR ANT OOR LRTS MSXNS ATNTNK
     0
        IF MSK B O FT OF LF PL ON JF M EKSSS OF IT OT ...
                                         WL Y K HNT M LRT
     2
                                                    HT KR
     3
     4
                                                     0 HRT
```

stemtext paragraphtype section \

```
enter duke orsino curio and other lord musicia...
                                                                          1.0
                                                                          1.0
  if music be the food of love plai on give me e...
2
                            will you go hunt my lord
                                                                            1.0
3
                                           what curio
                                                                            1.0
4
                                             the hart
                                                                            1.0
                                                                    b
   chapter charcount wordcount
0
       1.0
                  65.0
                              9.0
1
       1.0
                646.0
                            114.0
2
       1.0
                 27.0
                              6.0
3
       1.0
                 13.0
                              2.0
       1.0
                 10.0
                              2.0
```

Part a Connect to your local PostgreSQL server (take steps to hide your password!), create a new database for the Shakespeare data, use create\_engine() from sqlalchemy to connect to the database, and create the works, characters, chapters, and paragraphs tables populated with the data from the four dataframes shown above. [2 points]

```
[]: db_name = 'shakespeare_db'
     db_user = os.getenv('POSTGRES_USER')
     db_password = os.getenv('POSTGRES_PASSWORD')
     db_host = os.getenv('POSTGRES_HOST')
     db_port = os.getenv('POSTGRES_PORT')
     conn = psycopg2.connect(
         dbname='postgres',
         user=db_user,
         password=db_password,
         host=db_host,
         port=db port
     conn.autocommit = True
     cursor = conn.cursor()
     cursor.execute(f"CREATE DATABASE {db_name}")
     cursor.close()
     conn.close()
```

```
DuplicateDatabase

Cell In[9], line 17

14 conn.autocommit = True

15 cursor = conn.cursor()

---> 17 cursor.execute(f"CREATE DATABASE {db_name}")

18 cursor.close()

19 conn.close()
```

DuplicateDatabase: database "shakespeare\_db" already exists

[]: 475

Part b Write a query to display title, date, and totalwords from the works table. Rename date to year, and sort the output by totalwords in descending order. Also create a new column called era which is equal to "early" for works created before 1600, "middle" for works created between 1600 and 1607, and "late" for works created after 1607. Finally, display only the 7th through 11th rows of the output data. [1 point]

```
[]:
                      title year
                                   totalwords
                                                   era
    0
                  King Lear 1605
                                         26119 middle
      Troilus and Cressida 1601
                                         26089 middle
    1
    2
          Henry IV, Part II 1597
                                         25692
                                                early
          Henry VI, Part II 1590
    3
                                         25411
                                                 early
           The Winter's Tale 1610
                                         24914
                                                  late
```

Part c The genretype column in the "works" table designates five types of Shakespearean work:

- t is a tragedy, such as Romeo and Juliet and Hamlet
- c is a comedy, such as A Midsummer Night's Dream and As You Like It

- h is a history, such as Henry V and Richard III
- s refers to Shakespeare's sonnets
- p is a narrative (non-sonnet) poem, such as Venus and Adonis and Passionate Pilgrim

Write a query that generates a table that reports the average number of words in Shakepeare's works by genre type. Display the genre type and the average wordcount within genre, use appropriate aliases, and sort by the average in descending order. [1 point]

```
[]:
       genre
              average_wordcount
                    24236.000000
                    23817.363636
     1
           t
     2
           c
                    20212.071429
     3
                    17515.000000
           s
     4
                     6181.800000
           р
```

Part d Use a query to generate a table that contains the text of Hamlet's (the character, not just the play) longest speech, and use the print() function to display this text. [1 point]

Well said, old mole! Canst work i' th' earth so fast? [p]A worthy pioner! Once more remove, good friends.

#### 1.1.4 Part e

Many scenes in Shakespeare's works take place in palaces or castles. Use a query to create a table that lists all of the chapters that take place in a palace. Include the work's title, the section

(renamed to "act"), the chapter (renamed to "scene"), and the description of these chapters. The setting of each scene is listed in the description column of the "chapters" table. [Hint: be sure to account for case sensitivity] [2 points]

```
[]: query_e = """
     SELECT
         w.title,
         c.section AS act,
         c.chapter AS scene,
         c.description AS description
     FROM chapters c
     JOIN works w ON c.workid = w.workid
     WHERE LOWER(c.description) LIKE '%%palace%%';
     result_e = pd.read_sql_query(query_e, engine)
     result_e
[]:
                              title act
                                          scene \
     0
                      Twelfth Night 2.0
                                            4.0
```

```
1
                 Twelfth Night 1.0
                                        4.0
2
                 Twelfth Night 1.0
                                        1.0
     All's Well That Ends Well
                                5.0
3
                                        3.0
     All's Well That Ends Well 5.0
4
                                        2.0
120
             The Winter's Tale 5.0
                                        1.0
121
             The Winter's Tale 4.0
                                        2.0
122
             The Winter's Tale 2.0
                                        3.0
123
             The Winter's Tale 2.0
                                        1.0
124
             The Winter's Tale 1.0
                                        1.0
                                description
0
                     DUKE ORSINO's palace.
1
                     DUKE ORSINO's palace.
2
                     DUKE ORSINO's palace.
3
            Rousillon. The COUNT's palace.
     Rousillon. Before the COUNT's palace.
4
. .
120
                A room in LEONTES' palace.
121
         Bohemia. The palace of POLIXENES.
122
                A room in LEONTES' palace.
                A room in LEONTES' palace.
123
124
           Antechamber in LEONTES' palace.
```

[125 rows x 4 columns]

#### 1.1.5 Part f

Create a table that lists characters, the plays that the characters appear in, the number of speeches the character gives, and the average length of the speeches that the character gives. Display the character description and the work title, not the ID values. Sort the table by average speech length, and restrict the table to only those characters that give at least 20 speeches. [Hint: you will need to use a subquery.] [2 points]

```
[]: query_f = """
     SELECT
         c.charname AS character,
         w.title AS play,
         c.description,
         speech_stats.speech_count,
         speech_stats.avg_speech_length
     FROM characters c
     JOIN (
         SELECT
             charid,
             workid,
             COUNT(*) AS speech_count,
             AVG(wordcount) AS avg speech length
         FROM paragraphs
         GROUP BY charid, workid
         HAVING COUNT(*) >= 20
     ) AS speech_stats
     ON c.charid = speech_stats.charid
     JOIN works w
     ON speech_stats.workid = w.workid
     ORDER BY speech_stats.avg_speech_length DESC;
     result_f = pd.read_sql_query(query_f, engine)
     print(result_f)
```

```
character
                                              play \
0
                    Poet
                                           Sonnets
1
               Henry IV
                                  Henry IV, Part I
2
                    Poet
                               Passionate Pilgrim
3
               Henry IV
                                Henry IV, Part II
4
                                        Richard II
        King Richard II
447
     (stage directions)
                                 Romeo and Juliet
448
     (stage directions)
                                The Winter's Tale
449
     (stage directions)
                             Troilus and Cressida
450
     (stage directions)
                                     Twelfth Night
451
     (stage directions)
                          Two Gentlemen of Verona
```

description speech\_count avg\_speech\_length

0	the voice of Shakespeare's poetry	154	113.733766
1	King of England	30	85.900000
2	the voice of Shakespeare's poetry	43	72.651163
3	King of England	34	71.794118
4	king of England	98	61.765306
	<b></b>	•••	•••
447	None	146	3.342466
448	None	67	3.238806
449	None	158	2.936709
450	None	108	2.935185
451	None	86	2.500000

[452 rows x 5 columns]

### 1.1.6 Part g

Which Shakepearean works do not contain any scenes in a palace or a castle? Use a query that displays the title, genre type, and publication date of works that do not contain any scenes that take place in a palace or castle. [Hint: use your work in part e as a starting point. You will need a subquery, and you will need to think carefully about the type of join that you need to perform.][2 points]

```
[]: query_g = """
SELECT
    w.title,
    w.genretype,
    w.date AS publication_date
FROM works w
WHERE w.workid NOT IN (
    SELECT DISTINCT c.workid
    FROM chapters c
    WHERE LOWER(c.description) LIKE '%%palace%%'
    OR LOWER(c.description) LIKE '%%castle%'
);
"""

result_g = pd.read_sql_query(query_g, engine)
print(result_g)
```

	title	genretype	<pre>publication_date</pre>
0	Coriolanus	t	1607
1	Julius Caesar	t	1599
2	Lover's Complaint	р	1609
3	Love's Labour's Lost	С	1594
4	Merchant of Venice	С	1596
5	Merry Wives of Windsor	С	1600
6	Much Ado about Nothing	С	1598
7	Passionate Pilgrim	р	1598

8	Phoenix and the Turtle	p	1601
9	Rape of Lucrece	р	1594
10	Romeo and Juliet	t	1594
11	Sonnets	S	1609
12	Taming of the Shrew	С	1593
13	Tempest	С	1611
14	Timon of Athens	t	1607
15	Venus and Adonis	р	1593

#### 1.1.7 Problem 2

The following file contains JSON formatted data of the official English-language translations of every constitution currently in effect in the world:

[]:						tex	t country	7 \
	0	'Afghani	stan 2004	Preambl	.e \nIn t	he na	Afghanistan	
	1	'Albania	1998 (re	v. 2012)	Preamble	\nWe	Albania	
	2	'Andorra	1993	Preamble	\nThe Ando	rran P	Andorra	
	3	'Angola	2010	Preamble	\nWe, the p	eople …	Angola	
	4	'Antigua	and Barb	uda 1981	Preamble	\nWH	Antigua and Barbuda	
		_				•••		
	140	'Uzbekis	tan 1992	(rev. 2011)	Preambl	e \	Uzbekistan	
	141	'Viet Na	m 1992 (r	ev. 2013)	Preamble	\nI	Viet Nam	
	142	'Yemen 1	991 (rev.	2001) P	ART ONE. TH	E FOUN	Yemen	
	143	'Zambia	1991 (rev	. 2009)	Preamble	\nWE,	Zambia	
	144	'Zimbabw	re 2013	Preamble	\nWe the	people…	Zimbabwe	
		adopted	revised	reinstated	democracy			
	0	2004	NaN	NaN	0.372201			
	1	1998	2012.0	NaN	0.535111			
	2	1993	NaN	NaN	NaN			
	3	2010	NaN	NaN	0.315043			
	4	1981	NaN	NaN	NaN			
		•••	•••	•••	•••			
	140	1992	2011.0	NaN	0.195932			
	141	1992	2013.0	NaN	0.251461			
	142	1991	2001.0	NaN	0.125708			
	143	1991	2009.0	NaN	0.405497			
	144	2013	NaN	NaN	0.315359			

[145 rows x 6 columns]

The text of the constitutions are available from the Wolfram Data Repository. I also included scores that represent the level of democractic quality in each country as of 2016. These scores are

compiled by the Varieties of Democracy (V-Dem) project. Higher scores indicate greater levels of democratic openness and competition.

Part a Connect to your local MongoDB server and create a new collection for the constitution data. Use .delete\_many({}) to remove any existing data from this collection, and insert the data in const\_json into this collection. [2 points]

```
[]: mongo host = os.getenv('MONGO HOST')
     mongo port = int(os.getenv('MONGO PORT'))
     mongo_user = os.getenv('MONGO_INITDB_ROOT_USERNAME')
     mongo_password = os.getenv('MONGO_INITDB_ROOT_PASSWORD')
     try:
         client = MongoClient(mongo_host, mongo_port, username=mongo_user,_
      password=mongo_password, authSource='admin', serverSelectionTimeoutMS=5000)
         client.server_info()
         db = client['constitution_db']
         collection = db['constitutions']
         collection.delete_many({})
         collection.insert_many(const_json)
         print("Data inserted successfully into MongoDB collection.")
     except pymongo.errors.ServerSelectionTimeoutError as err:
         print(f"Error: Could not connect to MongoDB server: {err}")
     except pymongo.errors.OperationFailure as err:
         print(f"Error: Authentication failed: {err}")
```

Data inserted successfully into MongoDB collection.

Part b Use MongoDB queries and the dumps() and loads() functions from the bson package to produce dataframes with the following restrictions:

- The country, adoption year, and democracy features (and not \_id, text, revised, or reinstated) for countries with constitutions that were written after 1990
- The country, adoption year, and democracy features (and not \_id, text, revised, or reinstated) for countries with constitutions that were written after 1990 AND have a democracy score of less than 0.5
- The country, adoption year, and democracy features (and not \_id, text, revised, or reinstated) for countries with constitutions that were written after 1990 OR have a democracy score of less than 0.5

[1 point]

```
[]: query1 = {"adopted": {"$gt": 1990}}
projection = {"_id": 0, "country": 1, "adopted": 1, "democracy": 1}
results1 = collection.find(query1, projection)
```

```
df1 = pd.DataFrame(loads(dumps(results1)))
     df1
[]:
                       adopted democracy
             country
     0
         Afghanistan
                          2004
                                  0.372201
     1
             Albania
                          1998
                                  0.535111
     2
             Andorra
                          1993
                                       NaN
     3
              Angola
                          2010
                                  0.315043
     4
             Armenia
                          1995
                                  0.393278
     66
          Uzbekistan
                          1992
                                  0.195932
     67
            Viet Nam
                          1992
                                  0.251461
     68
                Yemen
                          1991
                                  0.125708
     69
              Zambia
                                  0.405497
                          1991
     70
            Zimbabwe
                          2013
                                  0.315359
     [71 rows x 3 columns]
[]: query2 = {"$and": [{"adopted": {"$gt": 1990}}, {"democracy": {"$lt": 0.5}}]}
     results2 = collection.find(query2, projection)
     df2 = pd.DataFrame(loads(dumps(results2)))
     df2
[]:
                                             adopted
                                    country
                                                       democracy
     0
                                Afghanistan
                                                 2004
                                                        0.372201
     1
                                     Angola
                                                 2010
                                                        0.315043
     2
                                    Armenia
                                                 1995
                                                        0.393278
     3
                                    Belarus
                                                 1994
                                                        0.289968
     4
                    Bosnia and Herzegovina
                                                 1995
                                                        0.338267
     5
                                   Cambodia
                                                 1993
                                                        0.313738
     6
                                      Egypt
                                                 2014
                                                        0.218600
     7
                         Equatorial Guinea
                                                 1991
                                                        0.217861
     8
                                                        0.075621
                                    Eritrea
                                                 1997
     9
                                   Ethiopia
                                                 1994
                                                        0.254865
     10
                                       Fiji
                                                 2013
                                                        0.473559
     11
                                                 1996
                                                        0.348132
                                     Gambia
     12
                                       Iraq
                                                 2005
                                                        0.455402
     13
                                 Kazakhstan
                                                 1995
                                                        0.262596
     14
         Lao People's Democratic Republic
                                                 1991
                                                        0.094434
     15
                                                 2011
                                                        0.294716
                                      Libya
     16
                                   Maldives
                                                 2008
                                                        0.386754
     17
                                 Montenegro
                                                 2007
                                                        0.455338
     18
                                    Myanmar
                                                 2008
                                                        0.405772
     19
                                       Oman
                                                 1996
                                                        0.191211
     20
                        Russian Federation
                                                 1993
                                                        0.275516
     21
                                     Rwanda
                                                 2003
                                                        0.274476
     22
                               Saudi Arabia
                                                 1992
                                                        0.024049
```

```
23
                                    Serbia
                                                2006
                                                        0.474443
     24
                                   Somalia
                                                2012
                                                        0.177772
     25
                               South Sudan
                                                2011
                                                        0.183267
     26
                                      Sudan
                                                2005
                                                        0.311799
     27
                                 Swaziland
                                                2005
                                                        0.136008
     28
                      Syrian Arab Republic
                                                2012
                                                        0.148212
     29
                              Turkmenistan
                                                2008
                                                        0.154887
     30
                                    Uganda
                                                1995
                                                        0.338308
                                   Ukraine
     31
                                                1996
                                                        0.361911
     32
                                Uzbekistan
                                                1992
                                                        0.195932
     33
                                  Viet Nam
                                                1992
                                                        0.251461
     34
                                      Yemen
                                                1991
                                                        0.125708
     35
                                     Zambia
                                                1991
                                                        0.405497
     36
                                  Zimbabwe
                                                2013
                                                        0.315359
[]: query3 = {"$or": [{"adopted": {"$gt": 1990}}, {"democracy": {"$lt": 0.5}}]}
     results3 = collection.find(query3, projection)
     df3 = pd.DataFrame(loads(dumps(results3)))
     df3
```

[]:		country	adopted	democracy
	0	Afghanistan	2004	0.372201
	1	Albania	1998	0.535111
	2	Andorra	1993	NaN
	3	Angola	2010	0.315043
	4	Armenia	1995	0.393278
		•••	•••	•••
	78	Uzbekistan	1992	0.195932
	79	Viet Nam	1992	0.251461
	80	Yemen	1991	0.125708
	81	Zambia	1991	0.405497
	82	Zimbabwe	2013	0.315359

[83 rows x 3 columns]

Part c According to the Varieties of Democracy project, Hungary has become less democratic over the last few years, and can no longer be considered a democracy. Update the record for Hungary to set the democracy score at 0.4. Then query the database to extract the record for Hungary and display the data in a dataframe. [1 point]

You will build a database and populate it with these data. The ER diagram for the database is:

There's no codebook, unfortunately, but the values in the columns are mostly self-explanatory:

```
[]: country adopted democracy 0 Hungary 2011 0.4
```

**Part d** Set the text field in the database as a text index. Then query the database to find all constitutions that contain the exact phrase "freedom of speech". Display the country name, adoption year, and democracy scores in a dataframe for the constitutions that match this query. [2 points]

		country	adopted	democracy	score
0		Myanmar	2008	0.405772	1.999446
1		Fiji	2013	0.473559	1.987625
2		Bangladesh	1972	0.369978	1.986046
3	Korea	(Republic of)	1948	0.757692	1.972244
4		Gambia	1996	0.348132	1.970934
5		Jordan	1952	0.270614	1.970513
6		Mexico	1917	0.672567	1.969448
7		Cyprus	1960	0.810509	1.969396
8		Ghana	1992	0.670849	1.939626
9		India	1949	0.632527	1.937849
10		Georgia	1995	0.757486	1.878084
11		China	1982	0.096066	1.877029
12		Hungary	2011	0.400000	1.876935
13		Sierra Leone	1991	0.564657	1.876923
14		South Africa	1996	0.727070	1.876189
15		Pakistan	1973	0.430273	1.875471
16		Philippines	1987	0.567393	1.867954
17		Singapore	1963	0.446464	1.812783
18		Malaysia	1957	0.345091	1.812688
19		Eritrea	1997	0.075621	1.755868
20		Zimbabwe	2013	0.315359	1.753159

```
21
                                             Kenya
                                                        2010
                                                                0.531911
                                                                          1.753046
                              Antigua and Barbuda
22
                                                        1981
                                                                     NaN
                                                                           1.752573
                                                                           1.751588
23
                            Saint Kitts and Nevis
                                                        1983
                                                                     NaN
24
                              Trinidad and Tobago
                                                        1976
                                                                0.730927
                                                                           1.751134
                                             Samoa
25
                                                        1962
                                                                     NaN
                                                                           1.750810
                                         Sri Lanka
26
                                                        1978
                                                                0.647035
                                                                           1.750668
27
                                 Marshall Islands
                                                        1979
                                                                     NaN
                                                                           1.735062
28
                                          Slovenia
                                                        1991
                                                                0.861380
                                                                           1.506431
29
                                                                0.682208
                                            Poland
                                                        1997
                                                                           1.505841
                                           Croatia
30
                                                        1991
                                                                0.710922
                                                                           1.505056
31
    Macedonia (The former Yugoslav Republic of)
                                                        1991
                                                                0.510983
                                                                           1.504414
                                                                0.262596
32
                                        Kazakhstan
                                                        1995
                                                                           1.503627
33
                                           Finland
                                                        1999
                                                                0.856265
                                                                           1.502870
34
                                             Spain
                                                        1978
                                                                0.834466
                                                                           1.502784
35
                                           Namibia
                                                        1990
                                                                0.745421
                                                                           1.502779
36
                Saint Vincent and the Grenadines
                                                        1979
                                                                     NaN
                                                                           1.502273
37
                                          Dominica
                                                        1978
                                                                     NaN
                                                                           1.502226
38
                                         Swaziland
                                                        2005
                                                                0.136008
                                                                           1.502019
                                              Peru
                                                                0.730816
                                                                           1.501971
39
                                                        1993
40
                                            Rwanda
                                                        2003
                                                                0.274476
                                                                           1.501947
                                 Papua New Guinea
41
                                                        1975
                                                                0.488884
                                                                           1.501847
42
                                            Belize
                                                        1981
                                                                     NaN
                                                                           1.501801
43
                                        Seychelles
                                                        1993
                                                                0.589139
                                                                           1.501721
                                                                0.338308
                                                        1995
44
                                            Uganda
                                                                           1.501426
45
                                           Somalia
                                                        2012
                                                                0.177772
                                                                           1.501224
46
                                           Liberia
                                                        1986
                                                                0.629972
                                                                           1.500673
47
                Lao People's Democratic Republic
                                                        1991
                                                                0.094434
                                                                           1.500575
48
                                            Bhutan
                                                        2008
                                                                0.537041
                                                                           1.497179
49
        Korea (Democratic People's Republic of)
                                                                0.090438
                                                        1972
                                                                           1.493815
50
                                             Tonga
                                                        1875
                                                                     NaN
                                                                           1.485681
51
                        United States of America
                                                        1789
                                                                0.849155
                                                                           1.250496
```

Part e Use a query to search for the terms "freedom", "liberty", "legal", "justice", and "rights". Generate a text score for all of the countries, and display the data for the countries with the top 10 relevancy scores in a dataframe. [2 points]

```
[]:
                      country
                               adopted
                                        democracy
                                                       score
     0
                       Serbia
                                  2006
                                          0.474443
                                                   5.030999
     1
                      Finland
                                  1999
                                          0.856265
                                                   5.029000
     2
                      Estonia
                                  1992
                                          0.909233 5.024473
     3
                      Armenia
                                  1995
                                          0.393278
                                                    5.023651
     4
                      Albania
                                  1998
                                          0.535111
                                                    5.023087
     5
           Dominican Republic
                                  2015
                                          0.583654 5.019910
     6
        Moldova (Republic of)
                                  1994
                                          0.571357
                                                    5.017063
     7
                  El Salvador
                                  1983
                                          0.661989
                                                    5.016899
     8
                      Georgia
                                  1995
                                          0.757486
                                                    5.015282
     9
                       Turkey
                                  1982
                                          0.341745 5.014672
```

## 1.1.8 Question 3

Close the connections to the PostgreSQL and MongoDB databases. [1 point]

```
[]: conn.close() client.close()
```