NLP Assignment #2 - Luke Schwenke

Note: records counts will be different, depending on when you query the API

In [ ]:
```
import pandas as pd
import requests
```

In [ ]:
```
%%time

# Define the API endpoint and parameters
url = "https://data.cityofchicago.org/resource/cwig-ma7x.json"

# Fetch the total count of records
def get_total_count(url):
    params = {
        "$select": "count(*)"
    }
    response = requests.get(url, params=params)
    data = response.json()
    return int(data[0]['count'])

total_count = get_total_count(url)
print(f"Total number of records available: {total_count:,.0f}")
```

```
Total number of records available: 266,229
CPU times: user 11.2 ms, sys: 5.28 ms, total: 16.4 ms
Wall time: 210 ms
```

In [ ]:
```
%%time

# Fetch data and load it into a pandas DataFrame
def fetch_data(url, params):
    response = requests.get(url, params=params)
    data = response.json()
    return pd.DataFrame(data)

# Set the limit parameter equal to the number of available records
params = {
    "$limit": total_count
}

# Fetch the data and load it into a DataFrame
df = fetch_data(url, params)

print(f'Number of records retrieved: {df.shape[0]:,.0f}')
```

```
Number of records retrieved: 266,229
CPU times: user 5.93 s, sys: 1.91 s, total: 7.83 s
Wall time: 28.9 s
```

In [ ]:
```
df.head(3)
```

Out[ ]:

	inspection_id	dba_name	aka_name	license_	facility_type	risk	address	
0	2588013	SOLOWAY COFFEE	SOLOWAY COFFEE	2938639	Restaurant	Risk 1 (High)	2275 N LINCOLN AVE	CHI
1	2588012	L & L ACADEMY AND PRESCHOOL	L & L ACADEMY AND PRESCHOOL	2443069	Children's Services Facility	Risk 1 (High)	1154-1158 W BELMONT AVE	CHI
2	2588015	DON MEMO MEXICAN RESTAURANT	DON MEMO MEXICAN RESTAURANT	2863378	Restaurant	Risk 1 (High)	10536 S TORRENCE AVE	CHI

3 rows × 22 columns

1. Filter the data for failed inspections and only keep records where Violations description is not blank.

In [ ]:
```
# Filter the results column to where the results are "Fails"
df_f = df[df.results=='Fail']
print("There are now", df_f.shape[0], "rows in the dataset after we subset t
```

```
There are now 51960 rows in the dataset after we subset to only Fail result
s. There were 266229 rows.
```

In [ ]:
```
df_c = df_f.dropna(subset=['violations'])
df_c = df_c.reset_index(drop=True)
print("There are now", df_c.shape[0], "rows in the dataset after removing Na
```

```
There are now 48530 rows in the dataset after removing NaN's from violations
```

2. Using regex, separate the violation description and comments into separate data frame columns.

In [ ]:
```
# VIOLATION DESCRIPTION

# First remove the numbers at the beginning
df_c['violation_description'] = df_c['violations'].str.replace(r'\d+|\.', ''
# Second remove the commends and initial whitespace
df_c['violation_description'] = df_c['violation_description'].str.replace(r'
df_c['violation_description'] = df_c['violation_description'].str.lstrip()
```

In [ ]:
```
# COMMENTS

df_c['comments'] = df_c['violations'].str.extract(r'Comments: (.*?)(?:\||$)'
```

In [ ]:
```
import re
def strip_multiple_spaces(string):
    return re.sub(r'\s+', ' ', string).strip()
# Strip columns to single spaces
df_c['violation_description'] = df_c['violation_description'].apply(lambda x
df_c['comments'] = df_c['comments'].astype(str).str.strip().str.replace('\s+
```

```
/var/folders/rx/2jqwhb8d31960xlz0g9vlmdh0000gn/T/ipykernel_47419/4187734932.
py:6: FutureWarning: The default value of regex will change from True to Fal
se in a future version.
  df_c['comments'] = df_c['comments'].astype(str).str.strip().str.replace('\
s+', ' ')
```

3. Tokenize violation description and comment columns

In [ ]:
```
import nltk
from nltk import word_tokenize

vds = df_c.violation_description.apply(lambda x: word_tokenize(x))
com = df_c.comments.apply(lambda x: word_tokenize(x))
```

4. Find top-10 tokens of each column

In [ ]:
```
from collections import Counter

vds_tokens = [token for tokens in vds for token in tokens]
com_tokens = [token for tokens in com for token in tokens]
```

In [ ]:
```
word_dist = nltk.FreqDist(vds_tokens)
df_word_dist = pd.DataFrame(word_dist.most_common(10),
                    columns=['Word', 'Frequency']).set_index('Word')

print("Top 10 Words BEFORE Cleaning - Violation Descriptions")
df_word_dist.head(10)
```

Top 10 Words BEFORE Cleaning - Violation Descriptions

Out[ ]:

Word	Frequency
,	372604
AND	172943
:	128985
FOOD	89359
MAINTAINED	89321
&	80609
PROPERLY	74608
CLEAN	71479
INSTALLED	69322
CONSTRUCTED	68318

In [ ]:
```
word_dist = nltk.FreqDist(com_tokens)
df_word_dist = pd.DataFrame(word_dist.most_common(10),
                    columns=['Word', 'Frequency']).set_index('Word')

print("Top 10 Words BEFORE Cleaning - Comments")
df_word_dist.head(10)
```

Top 10 Words BEFORE Cleaning - Comments

Out[ ]:

Word	Frequency
.	151092
,	74098
AND	64911
THE	52085
TO	48620
IN	39582
OF	38239
ON	35980
AT	35322
INSTRUCTED	24516

5. Clean each column: convert to lower case, remove stopwords, punctuation, numbers, etc

In [ ]:
```
stopwords = set(nltk.corpus.stopwords.words('english'))
```

In [ ]:
```
def nlp_cleaner(column_to_clean):

    # Remove single-character tokens (mostly punctuation)
    words = [word for word in column_to_clean if len(word) > 1]

    # Remove numbers
    words = [word for word in words if not word.isnumeric()]

    # Remove punctuation
    words = [word for word in words if word.isalpha()]

    # Lowercase all words (default_stopwords are lowercase too)
    words = [word.lower() for word in words]

    # Remove stopwords
    words = [word for word in words if word not in stopwords]

    return words
```

In [ ]:
```
vds_tokens_clean = nlp_cleaner(vds_tokens)
com_tokens_clean = nlp_cleaner(com_tokens)
```

6. Find Top-10 Tokens Again (After Cleaning)

In [ ]:
```
word_dist = nltk.FreqDist(vds_tokens_clean)

df_word_dist = pd.DataFrame(word_dist.most_common(10),
                    columns=['Word', 'Frequency']).set_index('Word')

print("Top 10 Words AFTER Cleaning - Violation Descriptions")
df_word_dist.head(10)
```

```
Top 10 Words AFTER Cleaning - Violation Descriptions
```

Out[ ]:

Word	Frequency
food	89359
maintained	89321
properly	74608
clean	71479
installed	69322
constructed	68318
equipment	64932
surfaces	51522
cleaning	48295
contact	47987

In [ ]:
```
word_dist = nltk.FreqDist(com_tokens_clean)

df_word_dist = pd.DataFrame(word_dist.most_common(10),
                    columns=['Word', 'Frequency']).set_index('Word')

print("Top 10 Words AFTER Cleaning - Comments")
df_word_dist.head(10)
```

```
Top 10 Words AFTER Cleaning - Comments
```

Out[ ]:

Word	Frequency
instructed	25851
observed	25283
violation	25124
food	24674
must	21070
issued	18562
citation	18279
area	17270
sink	15026
priority	13973

7. Find top-10 tokens after applying Porter stemming to the columns obtained in step 5

In [ ]:
```
porter = nltk.PorterStemmer()
```

In [ ]:
```
# Porter stem the cleaned Comments tokens
com_tokens_clean_porter_stemmed = [porter.stem(word) for word in com_tokens_
```

In [ ]:
```
# Porter stem the cleaned Violation Description tokens
vds_tokens_clean_porter_stemmed = [porter.stem(word) for word in vds_tokens_
```

In [ ]:
```
def get_top_n(tokens):
    word_dist = nltk.FreqDist(tokens)

    df_word_dist = pd.DataFrame(word_dist.most_common(10),
                        columns=['Word', 'Frequency']).set_index('Word')

    print(df_word_dist.head(10))
```

In [ ]:
```
print("Violence Descriptions - Top 10 Words AFTER Cleaning AND Porter Stemmi
get_top_n(vds_tokens_clean_porter_stemmed)
```

```
Violence Descriptions - Top 10 Words AFTER Cleaning AND Porter Stemming
           Frequency
Word
clean         147035
food           94615
maintain       92870
properli       74608
instal         69322
construct      68318
equip          64932
surfac         51522
contact        47987
use            42860
```

In [ ]:
```
print("Comments - Top 10 Words AFTER Cleaning AND Porter Stemming")
get_top_n(com_tokens_clean_porter_stemmed)
```

```
Comments - Top 10 Words AFTER Cleaning AND Porter Stemming
          Frequency
Word
food           31867
violat         27166
area           26221
instruct       25901
observ         25434
must           21071
issu           18742
sink           18584
citat          18351
provid         16590
```

8. Find top-10 tokens after applying Lancaster stemming to the columns obtained in step 5

In [ ]:
```
lancaster = nltk.LancasterStemmer()
```

In [ ]:
```
# Lancaster stem the cleaned Comments tokens
com_tokens_clean_lancaster_stemmed = [lancaster.stem(word) for word in com_t
```

In [ ]:
```
# Lancaster stem the cleaned Violation Description tokens
vds_tokens_clean_lancaster_stemmed = [lancaster.stem(word) for word in vds_t
```

In [ ]:
```
print("Violence Descriptions - Top 10 Words AFTER Cleaning AND Lancaster Ste
get_top_n(vds_tokens_clean_lancaster_stemmed)
```

```
Violence Descriptions - Top 10 Words AFTER Cleaning AND Lancaster Stemming
           Frequency
Word
cle           156544
food           94615
maintain       92870
prop           92799
instal         69322
construct      68318
equip          64932
surfac         51522
contact        47987
us             42860
```

In [ ]:
```
print("Comments - Top 10 Words AFTER Cleaning AND Lancaster Stemming")
get_top_n(com_tokens_clean_lancaster_stemmed)
```

```
Comments - Top 10 Words AFTER Cleaning AND Lancaster Stemming
          Frequency
Word
food           31867
viol           27188
instruct       25903
observ         25435
found          21573
must           21071
issu           18742
sink           18584
cit            18362
are            17270
```

9. Find top-10 tokens after applying lemmatization to the columns obtained in step 5

In [ ]:
```
wnl = nltk.WordNetLemmatizer()
```

In [ ]:
```
# Lemmatize the cleaned Comments tokens
com_tokens_clean_lemmatized = [wnl.lemmatize(word) for word in com_tokens_cl
```

In [ ]:
```
# Lemmatize the cleaned Violence Description tokens
vds_tokens_clean_lemmatized = [wnl.lemmatize(word) for word in vds_tokens_cl
```

In [ ]:
```
print("Violence Descriptions - Top 10 Words AFTER Cleaning AND Lemmatizing")
get_top_n(vds_tokens_clean_lemmatized)
```

```
Violence Descriptions - Top 10 Words AFTER Cleaning AND Lemmatizing
             Frequency
Word
food             94615
maintained       89321
properly         74608
clean            71479
installed        69322
constructed      68318
equipment        64932
surface          51522
cleaning         48295
contact          47987
```

In [ ]:
```
print("Comments - Top 10 Words AFTER Cleaning AND Lemmatizing")
obj = get_top_n(com_tokens_clean_lemmatized)
```

```
Comments - Top 10 Words AFTER Cleaning AND Lemmatizing
            Frequency
Word
food             31866
violation        27163
area             26221
instructed       25851
observed         25283
must             21070
sink             18584
issued           18562
citation         18349
door             14370
```

10. Compare top-10 tokens obtained in 4, 6, 7, 8, 9.

11. Describe which approach provided the most comprehensive view of violations / comments and why

Summary: The top tokens in (4) returned a lot of punctuation because the data was uncleaned -- these tokens were not valuable. After cleaning, (6) (just cleaning) this method showed better results (7) (Porter Stemming) where results are mixed because we see some results like "properli" and "provid". The results with (8) (Lancaster Stemming) were slightly worse than Porter Stemming where we see words like "issu" and "cit". Lastly, (9) Lemmatize performed the best in terms of word clarity. This makes sense because stemming is primarily for speed and very large datasets wherease lemmatizing can be used if you have the time and processing power as it doesn't truncate words in the same way.

Answer: The top-10 tokens resulting from (9) Lemmatizing provided the most comprehensive view because the words displayed are clear, there is not punctuation included since it had been cleaned, and it preserved full words unlike the stemming methods did.

12. Use the "most effective" cleaning approach to plot the distribution of most common tokens (belonging to violation description) over time

In [ ]:
```
# Extract the top 10 most common words from the Lemmatized Violation Descrip
word_dist = nltk.FreqDist(vds_tokens_clean_lemmatized)#vds_tokens_clean)

vds_word_dist = pd.DataFrame(word_dist.most_common(10),
                    columns=['Word', 'Frequency'])

# Convert the top 10 words to a list
vds_10 = vds_word_dist.Word.to_list()
print(vds_10)
```

```
['food', 'maintained', 'properly', 'clean', 'installed', 'constructed', 'equ
ipment', 'surface', 'cleaning', 'contact']
```

In [ ]:
```
# Convert inspection_date to a date/time format
from datetime import datetime
df_c['inspection_date'] = pd.to_datetime(df_c['inspection_date'], format='%Y
```

In [ ]:
```
# Extract year from inspection date
df_c['Year'] = df_c['inspection_date'].dt.strftime('%Y')
```

In [ ]:
```
# Create a new dataframe with the year and lemmatized tokens
year_descriptions = pd.DataFrame(list(zip(df_c['Year'], vds_tokens_clean_lem
                  columns=['Year', 'tokens'])
```

In [ ]:
```
# Ensure there is a single row for each year/token combination
year_descriptions = year_descriptions.explode('tokens')
```

In [ ]:
```
# Filter to only tokens in our top 10 list
year_descriptions_10 = year_descriptions[year_descriptions['tokens'].isin(vd
```

In [ ]:
```
# For each year, count the number of tokens and store in a final dataframe f
year_descriptions_10_summary = year_descriptions_10.groupby(['Year', 'tokens
```

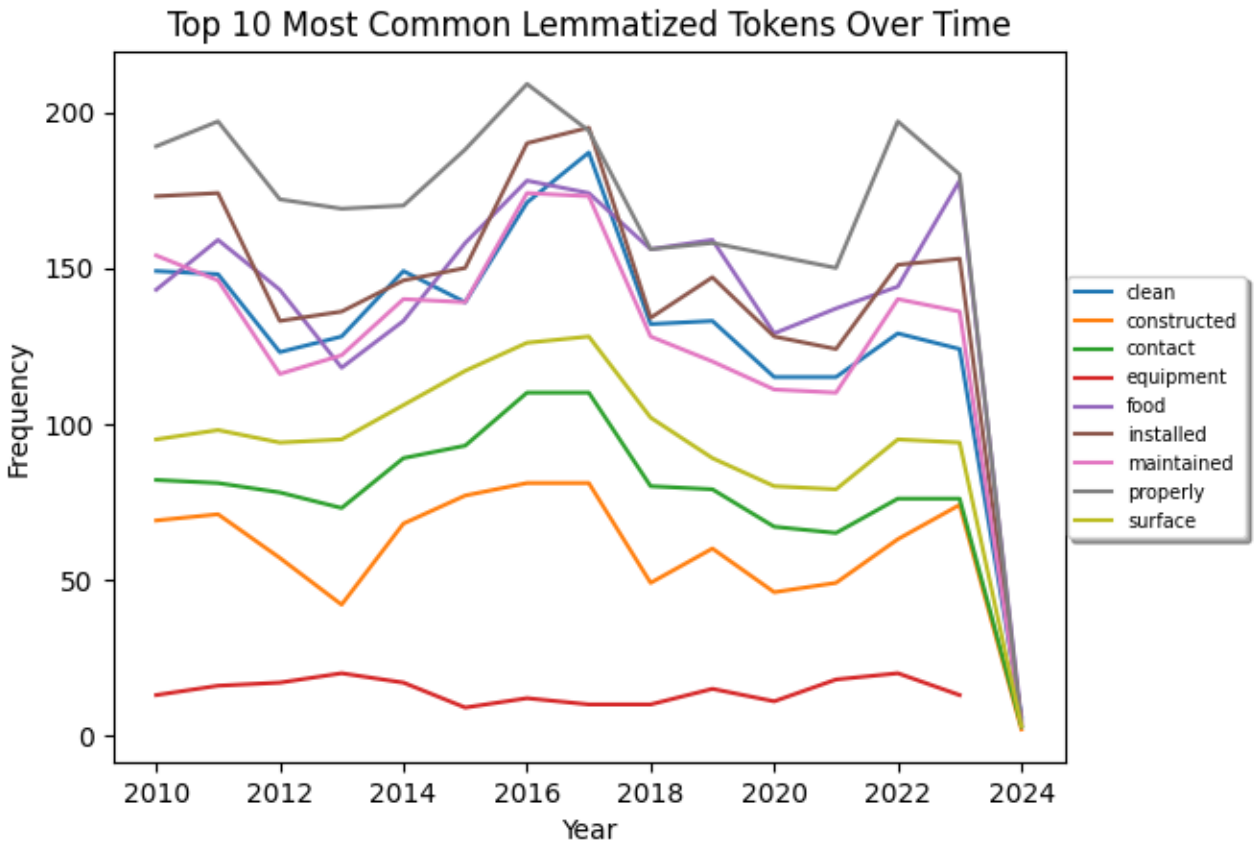
In [ ]:
```
year_descriptions_10_summary.head(10)
```

Out[ ]:

	Year	tokens	Count
0	2010	clean	149
1	2010	constructed	69
2	2010	contact	82
3	2010	equipment	13
4	2010	food	143
5	2010	installed	173
6	2010	maintained	154
7	2010	properly	189
8	2010	surface	95
9	2011	clean	148

In [ ]:
```
# Drop 2024 since the data is too new and there are too few records
year_descriptions_10_summary = year_descriptions_10_summary[year_description
```

In [ ]:
```
import matplotlib.pyplot as plt
year_descriptions_10_summary.pivot(index="Year", columns="tokens", values="C
ax = plt.subplot(111)
ax.legend(loc='center right', bbox_to_anchor=(1.2, 0.5),
          fancybox=True, shadow=True, fontsize="7")
plt.title('Top 10 Most Common Lemmatized Tokens Over Time')
plt.ylabel('Frequency')
plt.show()
```


Top 10 Most Common Lemmatized Tokens Over Time
Frequency
Year
0
50
100
150
200
2010
2012
2014
2016
2018
2020
2022
2024
clean
constructed
contact
equipment
food
installed
maintained
properly
surface

In [ ]:
```
# def new_dispersion_plot(text, words, ignore_case=False, title="Lexical Dis
#     """
#     Generate a lexical dispersion plot.

#     :param text: The source text
#     :type text: list(str) or iter(str)
#     :param words: The target words
#     :type words: list of str
#     :param ignore_case: flag to set if case should be ignored when searchi
#     :type ignore_case: bool
#     :return: a matplotlib Axes object that may still be modified before pl
#     :rtype: Axes
#     """

#     try:
#         import matplotlib.pyplot as plt
#     except ImportError as e:
#         raise ImportError(
#             "The plot function requires matplotlib to be installed. "
#             "See https://matplotlib.org/"
#         ) from e

#     word2y = {
#         word.casefold() if ignore_case else word: y
#         for y, word in enumerate(reversed(words))
#     }
#     xs, ys = [], []
#     for x, token in enumerate(text):
#         token = token.casefold() if ignore_case else token
#         y = word2y.get(token)
#         if y is not None:
#             xs.append(x)
#             ys.append(y)

#     _, ax = plt.subplots()
#     ax.plot(xs, ys, "|")
#     #ax.set_yticks(list(range(len(words))), words, color="C0") # Broken
#     ax.set_yticks(list(range(len(words))), list(word2y.keys()), color="C0"
#     ax.set_ylim(-1, len(words))
#     ax.set_title(title)
#     ax.set_xlabel("Word Offset")
#     return ax
```

In [ ]:
```
# import matplotlib.pyplot as plt

# dispersion = new_dispersion_plot(vds_tokens_clean_lemmatized, vds_10, titl

# plt.show()
```