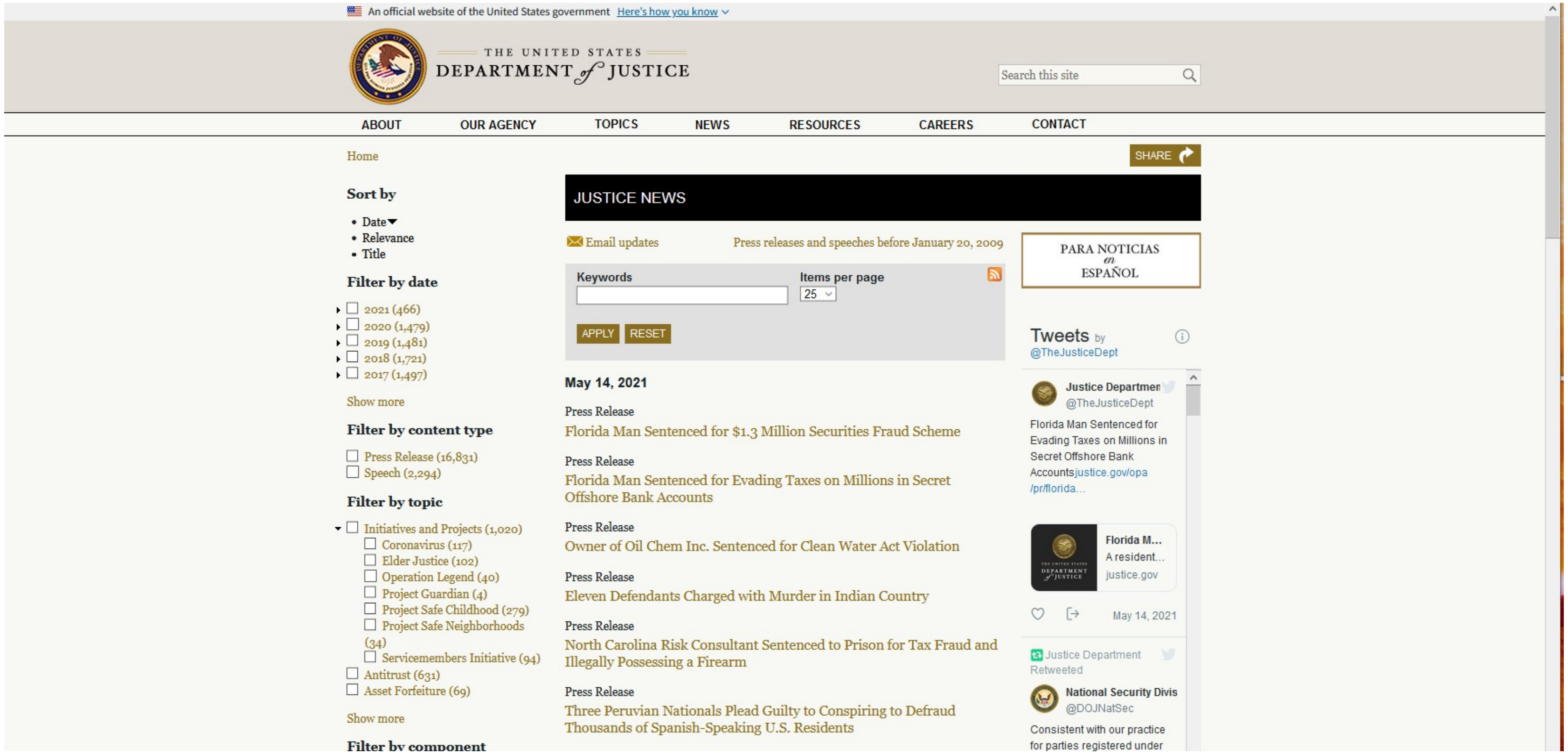
Natural Language Processing of DOJ Press Releases

by Matthew Quander

Introduction

- US Department of Justice regularly publishes press releases to inform the general public about active criminal prosecutions, civil enforcements, initiatives and projects, and any other non-sensitive information
- From 2009 to 2018, the DOJ was under 2 different administrations and was led by 3 different Attorneys General (2 from 1 administration)
- Since AGs are appointed by the president, political influence over the Department is often suspected
- *What has been the trend in cases brought by the Department from 2009 to 2018?*

justice.gov/news



- Kaggle dataset: Department of Justice 2009-2018 Press Releases
- As a former contractor to the Financial Fraud Section of the DOJ, I contributed to some of these cases
- By using Python's Natural Language Processing tools, and its Machine Learning and Clustering algorithms, I hope to uncover trends in the cases brought by the Justice Department within this timeframe

Dataset Description

- Kaggle dataset consists of 13,087 press releases from justice.gov/news, ranging from 2009-2018
- Data set provider scapped the data using a Python script and organized it into JSON format:
    - **id**: press release number
    - **title**: title of the release
    - **contents**: the full text of the press release
    - **date**: date the press release was posted on the website
    - **topics**: a set of topics covered by the release, if provided
    - **components**: a set of the agencies and departments involved in the particular release, if provided

- All fields populated with string data, common for NLP to operate on
- “id” field arbitrary number, “title” and “contents” fields most text heavy
- “date” field provided useful context in sequencing when cases brought and to investigate trends
- “topics” and “components” could provide insight into the type of case prior to processing the “contents” of the record

Exploratory Data Analysis

- used panda's `read_json` function to create a dataframe
- used several functions to check for null and missing values:

```
Blank Field Values:
id:  0 (227 null)
title:  0
contents:  2
date:  0
topics:  8399
components:  18
```

- ~64% of the records have missing values in “topics” attribute
- ~0.015% missing “contents”; ~0.138% missing “components”

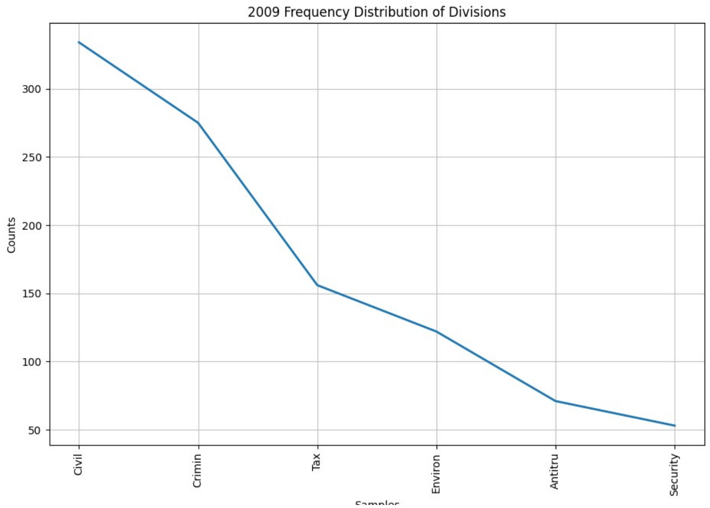
- Importing `nltk` library, used `stem`, `sub`, and `lower` functions to process the string of the “contents” field and remove stop words

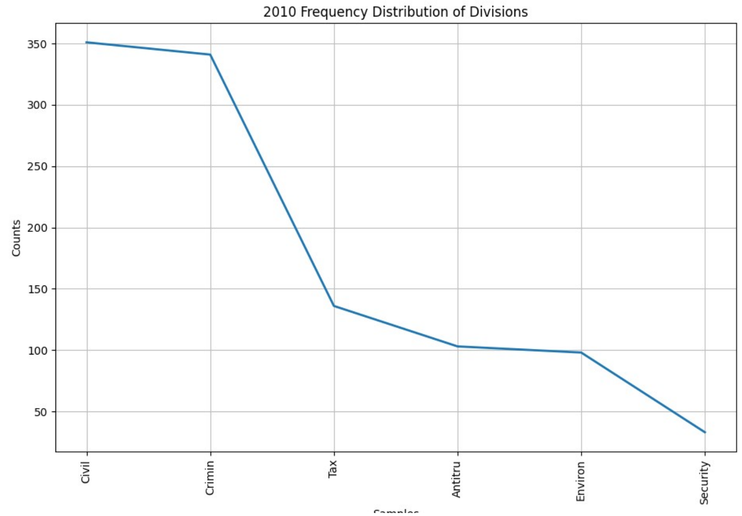
```
articles_df['cleaned content'] = articles_df['contents'].apply(lambda x: " ".join([stemmer.stem(i)
                                          for i in re.sub("[^a-zA-Z]", " ", x).split()
                                              if i not in stop_words]).lower())
```

- Created 10 separate dataframes by year, 2009-2018
- Declared set of litigating divisions: {Antitrust, Civil, Criminal, Environmental and Natural Resources, National Security, and Tax}
    - ignored administrative divisions in the press releases (e.g. JMD)

Frequency Distribution

```
2009 freqDist:
{'Antitru': 71, 'Civil': 334, 'Crimin': 275, 'Environ': 122, 'Security': 53, 'Tax': 156}
2010 freqDist:
{'Antitru': 103, 'Civil': 351, 'Crimin': 341, 'Environ': 98, 'Security': 33, 'Tax': 136}
2011 freqDist:
{'Antitru': 113, 'Civil': 383, 'Crimin': 478, 'Environ': 94, 'Security': 38, 'Tax': 220}
2012 freqDist:
{'Antitru': 92, 'Civil': 407, 'Crimin': 431, 'Environ': 91, 'Security': 25, 'Tax': 196}
2013 freqDist:
{'Antitru': 71, 'Civil': 380, 'Crimin': 371, 'Environ': 82, 'Security': 11, 'Tax': 227}
2014 freqDist:
{'Antitru': 88, 'Civil': 376, 'Crimin': 419, 'Environ': 68, 'Security': 31,  'Tax': 230}
2015 freqDist:
{'Antitru': 82, 'Civil': 420, 'Crimin': 343, 'Environ': 94, 'Security': 156, 'Tax': 276}
2016 freqDist:
{'Antitru': 105, 'Civil': 357, 'Crimin': 306, 'Environ': 74, 'Security': 130, 'Tax': 292}
2017 freqDist:
{'Antitru': 81, 'Civil': 292, 'Crimin': 347, 'Environ': 80, 'Security': 99, 'Tax': 256}
2018 freqDist:
{'Antitru': 33, 'Civil': 204, 'Crimin': 265, 'Environ': 37,  'Security': 76, 'Tax': 125}
```


2009 Frequency Distribution of Divisions
Counts
Civil
Crimin
Tax
Environ
Antitru
Security


2010 Frequency Distribution of Divisions
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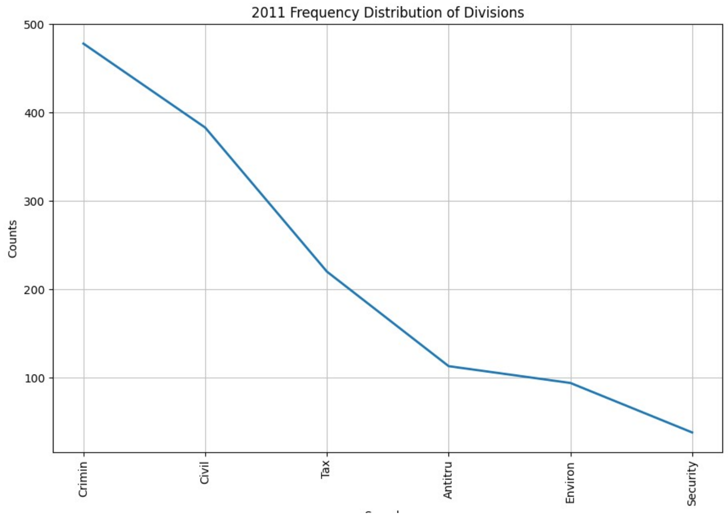
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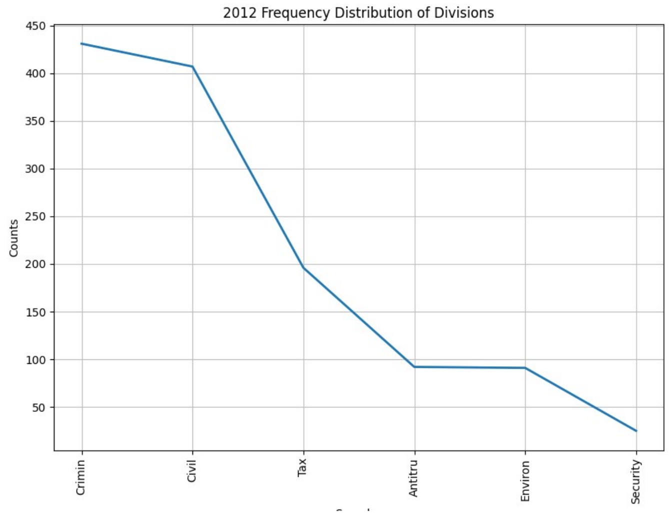
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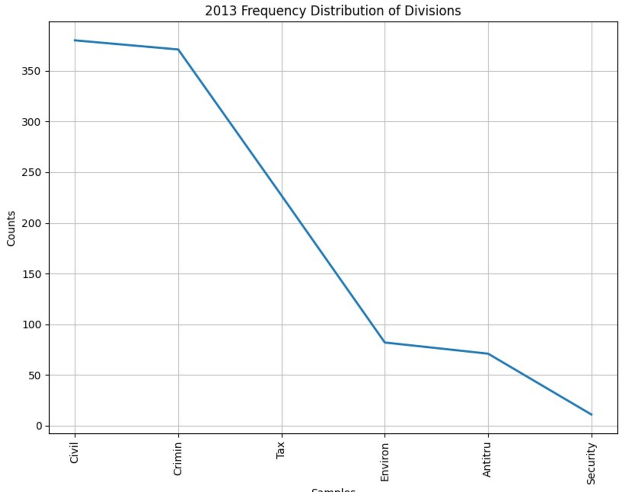
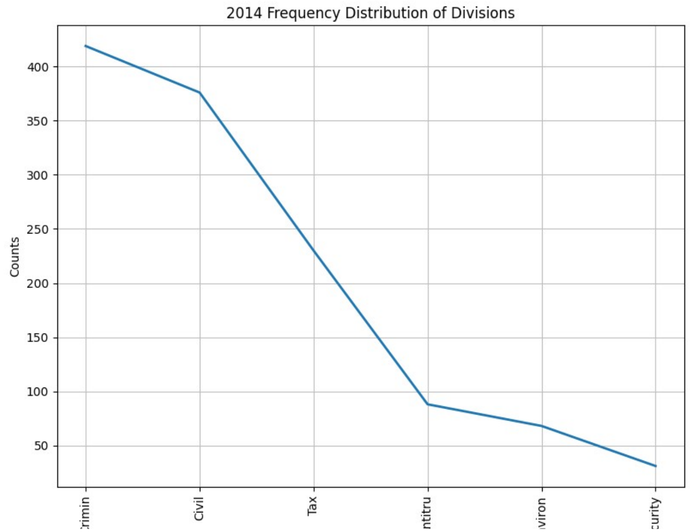
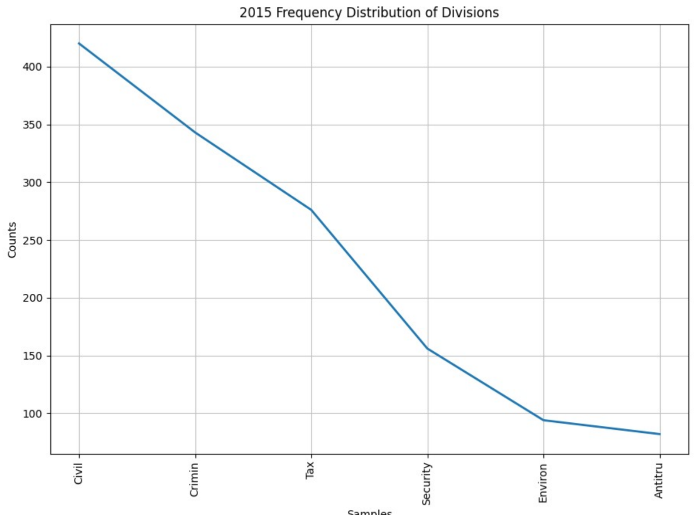

2013 Frequency Distribution of Divisions
Counts
350
300
250
200
150
100
50
0
Civil
Crimin
Tax
Environ
Antitru
Security


2014 Frequency Distribution of Divisions
Counts
400
350
300
250
200
150
100
50
Civil
Tax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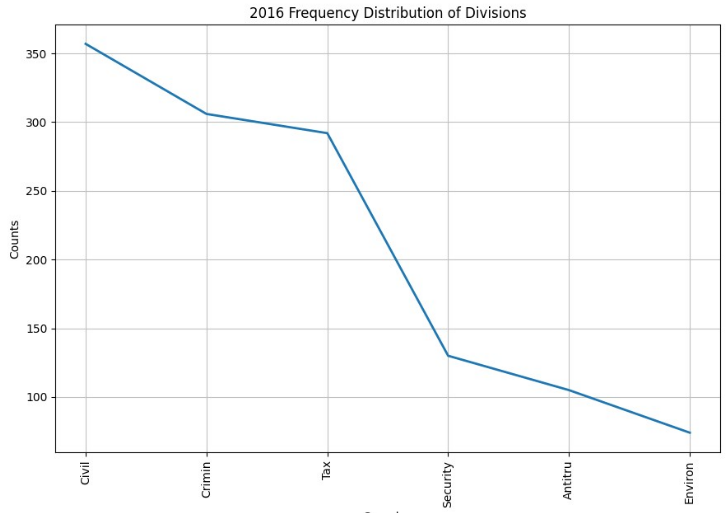
2016 Frequency Distribution of Divisions
Counts
350
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250
200
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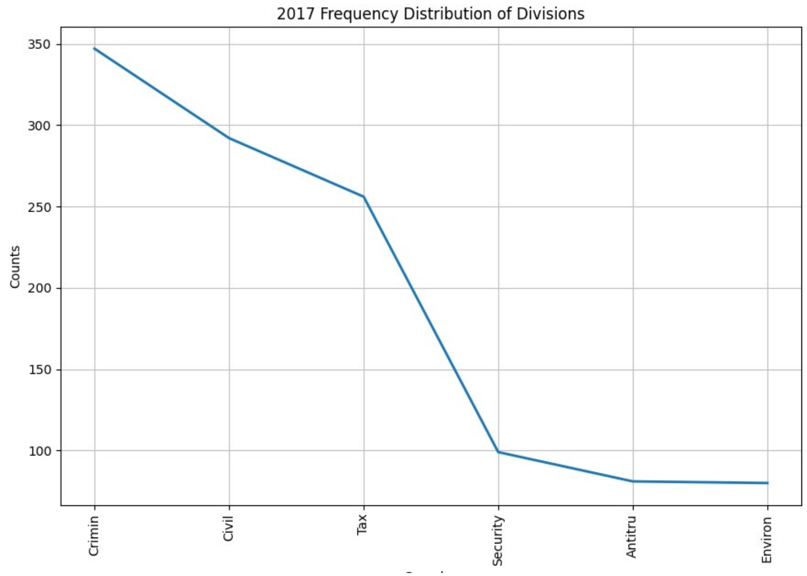
2017 Frequency Distribution of Divisions
Counts
350
300
250
200
150
100
Crimin
Civil
Tax
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Antitru
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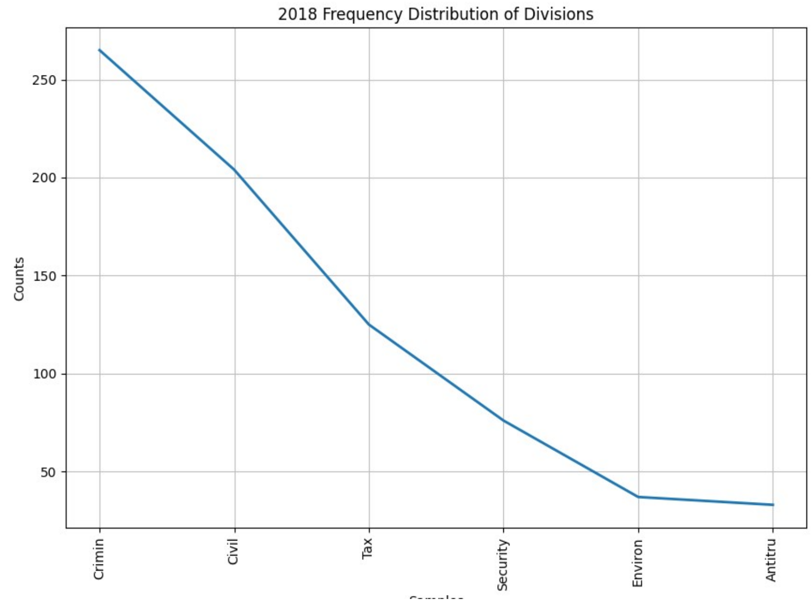
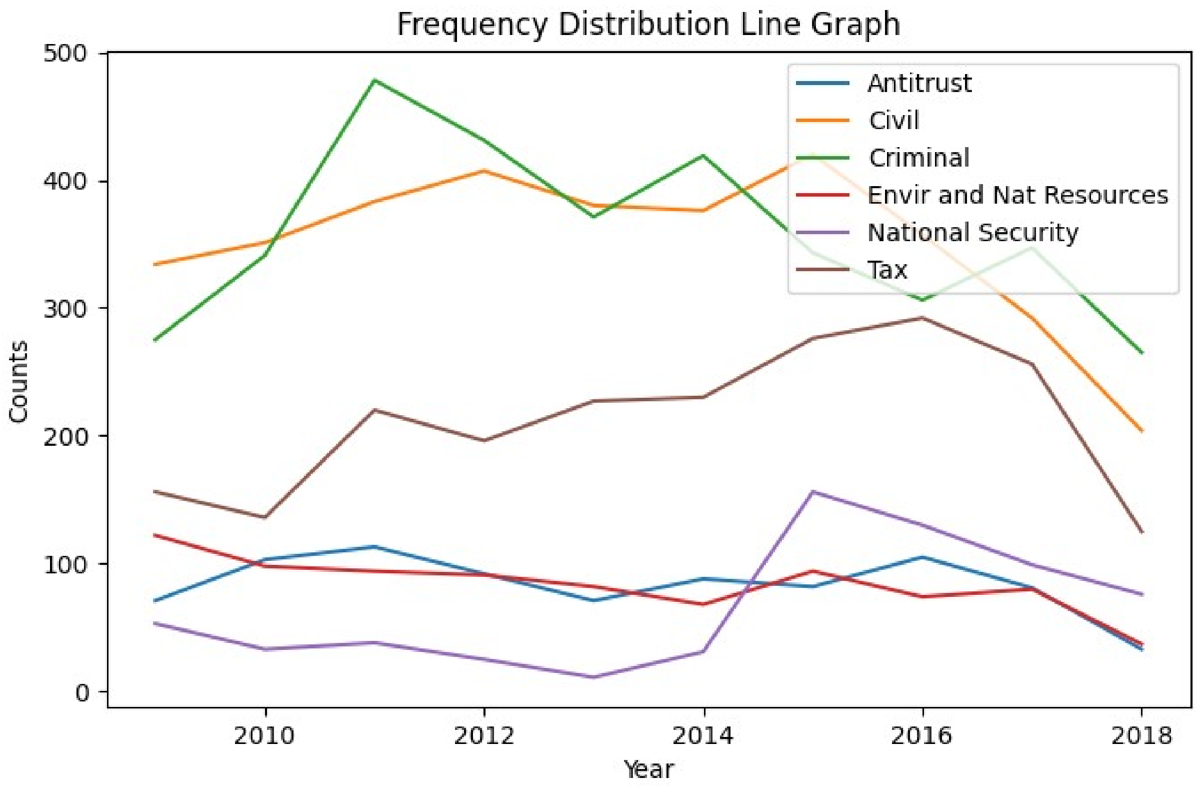

2018 Frequency Distribution of Divisions
Counts
250
200
150
100
50
Crimin
Civil
Tax
Security
Environ
Antitru

Aggregate Frequency Distribution



Word Cloud

- Visual display of commonly used words
  - joined strings of each row using `cat` function, passed entired string to `word_tokenize` function
  - removed words of 3 or less characters and removed common words (e.g. “attorney”, “department”, “justice”, etc.)
  - ex: 2011 and 2017

Experiment

- Term Frequency – Inverse Document Frequency (TF-IDF)
  - Term Frequency - the number of times a word appears in a document, divided by the total number of words in that document
  - Inverse Document Frequency - the log of, the total number of documents divided by the number of documents that contain a certain word w

$TF = \Sigma w/d$

w=word, d=total words in document

$IDF = \log(N/D(w))$

N=number of document, D(w)=number of documents containing word w

$TF\text{-}IDF = TF * IDF$

TF-IDF

- TF-IDF score for a word will initially increase if frequency is high within a document, but then decrease if the word is frequent throughout the data set
  - due to the IDF factor of the formula
- Words with higher TF-IDF score will be more relevant for specific topics of interest
- From Python's `sklearn` library, used `CountVectorizer`, `TfidfVectorizer`, and `TfidfTransformer` packages

TF-IDF 2010	
vehicl	0.494134
emiss	0.458472
test	0.290667
air	0.235928
nevada	0.204033
clean	0.156728
falsifi	0.143278
falsif	0.122377
analyz	0.116405

TF-IDF 2016	
visa	0.525740
harbor	0.325162
alien	0.321206
conspiraci	0.227706
student	0.218689
unnj	0.200166
profit	0.190308
new	0.165527
jersey	0.153425
fraud	0.145062

TF-IDF 2018	
site	0.480124
epa	0.290745
cleanup	0.283443
centredal	0.236808
river	0.224689
manor	0.207207
superfund	0.206141
emhart	0.177606
settlement	0.159827
woonasquatucket	0.148005

- 2010 - “vehicle” has highest score of ~0.49, followed by “emissions,” “test,” and “air.” Suggests case related to vehicle emissions scandal was unique for the year 2010
- 2016 - “visas” has highest score of ~0.53, followed by “harbor,” “alien,” “conspiracy,” and “student.” Correlation of terms suggests a unique case involving fraudulent student visas
  - “fraud” has lower score likely because it's used frequently in the data set
- 2018 - “site” has highest score of ~0.48, followed by “epa”, “cleanup” and “river.” Suggests unique case(s) with EPA and ENRD (DOJ) related to hazardous waste spill

Support Vector Machine

- Attempt to predict the “components” field based on the text of the “contents” field
  - Created sub-data frame of only the litigating DOJ entities
- Used the `train_test_split` function with the “cleaned contents” and “cleaned components” fields, with a 70-30 training-test split
  - SVM requires int values for classification labels, so converted them with the `fit_transform` function
- From the `svm` module, used the `SVC` to build hyperplane and fit the training set attributes and the training set labels
- Then called the `predict` and `accuracy_score` functions, resulted in a ~99.3% accuracy.

SVM code

test.py > ...

```python


train_X, test_X, train_Y, test_Y = model_selection.train_test_split(sub_df['cleaned content'], sub_df['cleaned components'], test_siz
encoder = LabelEncoder()
#print(train_X[0:12])

train_Y = encoder.fit_transform(train_Y)
test_Y = encoder.fit_transform(test_Y)
print("train_Y type: ", type(train_Y))
print("train_Y head: ", train_Y[0:22])

tfIdfVectorizer=TfidfVectorizer() #use_idf=True
tfIdfVectorizer.fit(sub_df['cleaned content'])

train_X_tfidf = tfIdfVectorizer.transform(train_X)
test_X_tfidf = tfIdfVectorizer.transform(test_X)


print("train_X_tfidf type: ", type(train_X_tfidf))

SVM = svm.SVC(C=1.0, kernel='linear', degree=3, gamma='auto')
SVM.fit(train_X_tfidf, train_Y)
predictions_SVM = SVM.predict(test_X_tfidf) # predict the labels on validation dataset
print("SVM Accuracy Score -> ", accuracy_score(predictions_SVM, test_Y)*100) # Use accuracy_score function to get the accuracy
```

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL 2: Python

```
3     9   15-089  ...  defend admit to target parent of hospit childr...     Criminal Division
4    10   14-660  ...  dure past week fbi local state feder law enfor...     Criminal Division

[5 rows x 8 columns]
train_Y type:  <class 'numpy.ndarray'>
train_Y head:  [2 1 4 1 4 3 3 3 3 1 0 1 2 2 3 1 2 3 3 0 1 2]
train_X_tfidf type:  <class 'scipy.sparse.csr.csr_matrix'>
SVM Accuracy Score ->  99.3
```

K-Means Clustering

- Used to group the articles' text into similar groups
  - used the `fit_transform` function on “cleaned contents” field
- Created an object from the `MiniBatchKMeans` class and obtained the top keywords
- “cleaned contents” text then grouped by the cluster object declared
- predetermined value of k = 10 clusters

```
Cluster 0
price,consum,acquisit,settlement,workshop,depart,merger,propos,competit,antitrust
Cluster 1
indict,racket,isil,polic,charg,attorney,terrorist,murder,member,gang
Cluster 2
polic,indict,traffick,inmat,assault,attorney,offic,civil,victim,right
Cluster 3
imag,ceo,safe,children,project,childhood,sexual,exploit,pornographi,child
Cluster 4
attorney,injunct,file,fals,refund,incom,ir,prepar,return,tax
Cluster 5
access,depart,civil,vote,employ,ada,disabl,hous,right,discrimin
Cluster 6
investig,attorney,briberi,govern,offici,armi,compani,bribe,crimin,contract
Cluster 7
claim,bill,oig,medic,patient,hhs,fraud,care,health,medicar
Cluster 8
communiti,general,nation,offic,justic,law,drug,state,depart,attorney
Cluster 9
conspir,conspiraci,account,attorney,crimin,charg,tax,financi,bank,fraud
```

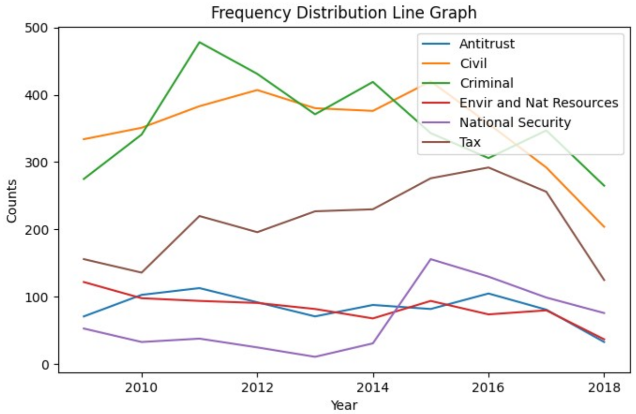
- Some words better clustered than others, e.g. Cluster 2 has terms “trafficking,” “inmate,” “civil,” and “right” - wide variety of cases
  - Similarly, Cluster 8 has general terms “general,” “nation,” “justice,” and “attorney”
- More accurate clusters are Cluster 3 which deals with child exploitation and Cluster 7 which deals with healthcare fraud

Results Analysis

- From the experiments, much information can be derived:
  - TF-IDF revealed the press releases of cases that were reported on less
    - done so by giving a higher score to words that were frequent in a document but infrequent throughout the data set
  - SVM successfully predicted the “components” field given the corresponding “contents” field
    - done so by splitting the data into a training and test set and learning from the training set
  - Clustering was less informative, case type of some clusters was easily discernable while others were inconclusive
    - likely due to the general words captured which could have manipulated the algorithm

Conclusion

- TF-IDF, SVM, and K-Means Clustering all proved effective in gaining information from the data set
- The NLP tools built into them gave an advantage in analyzing 13,087 records
- However, the tool which could answer the posed question was the frequency distribution



- Aggregate decline in press releases from 2016 to 2018, implying a decline in cases brought by the Department
- Actual cause remains unknown
  - could be funding, cooperation agreements, lack of evidence, or other reasons
  - requires further study

References

- [1] Department of Justice 2009-2018 Press Releases, Kaggle, July 29, 2018. [Online]. Available: https://www.kaggle.com/jbencina/department-of-justice-20092018-press-releases
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- [4] C. Silva. “Headlines Articles Analysis and NLP.” Towards Data Science. https://towardsdatascience.com/headlines-articles-analysis-and-nlp-4013a66dbac (accessed Apr. 8, 2021).
- [5] Qaiser, Shazad & Ali, Ramsha. “Text Mining: Use of TF-IDF to Examine the Relevance of Words to Documents,” in International Journal of Computer Applications, July 2018. [Online]. Available: https://www.researchgate.net/publication/326425709_Text_Mining_Use_of_TF-IDF_to_Examine_the_Relevance_of_Words_to_Documents
- [6] G. Bedi. “A guide to Text Classification(NLP) using SVM and Naïve Bayes with Python.” Medium. <link> (accessed May 5, 2021).