509 Final Project

- Import Libraries
- Define Functions
- Load MASTER data and/or Business Data
- Pre-Processing
- EDA
- Linear SVC Train/Test
- SKLEARN Linear SVC Train/Test
- Linear SVC Business Data Results

Globally import libraries

In [385…

```
#! pip install pyLDavis

import pyLDAvis

pyLDAvis.enable_notebook()
from tqdm.auto import tqdm
import spacy
import pyLDAvis.lda_model
import pyLDAvis.gensim_models

import numpy as np
import pandas as pd
import pymysql as mysql
import matplotlib.pyplot as plt
import os
import shutil
import re
import logging
import time
import zipfile
import requests
from bs4 import BeautifulSoup
import datetime
import re
import regex as rex
from collections import defaultdict, Counter
import random
import requests
from bs4 import BeautifulSoup
import datetime
import json
from wordcloud import WordCloud
from tabulate import tabulate
from sklearn.svm import SVC
import textacy.preprocessing as tprep
from textacy.extract import keyword_in_context

import sqlite3
import nltk
from string import punctuation
from nltk.corpus import stopwords
import re
import emoji
from nltk.metrics import ConfusionMatrix
import itertools
import collections
import pickle

from sklearn.model_selection import train_test_split
```

```
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.decomposition import NMF
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, f1_score, recall_score, precision_recall_curve
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.model_selection import GridSearchCV

## Depracated:
# from sklearn.metrics import plot_confusion_matrix
## New version:
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.model_selection import cross_val_score
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.svm import LinearSVC
from sklearn.decomposition import LatentDirichletAllocation

#import mysql.connector

# Set pandas global options
pd.options.display.max_rows = 17

import warnings
warnings.filterwarnings('ignore')
warnings.simplefilter('ignore')
```

Functions:

Data pre-processing:

REGEX and NORMALIZE FUNCTIONS

In [211…

```
rex_sep = rex.compile(r' ')
rex_ucode = rex.compile(r'[\\]u20*')

'''re.sub lambda citation:
https://chat.openai.com/share/402ec66e-2802-4cda-af8c-6f9f5b097d85
'''
sep_lst = []
ucode_lst = []
# Add leading and trailing space to URLs
def rex_replace(text):
    #txt = str(text)
    #print(lambda x: x.replace(' ', ' '))
    #sep_lst.append(rex_sep.findall(txt))
    #ucode_lst.append(rex_ucode.findall(txt))
    text = text.replace(r' ', ' ').replace(r'-', ' ')\
    .replace(r'\n', ' ').replace('\u2063', ' ').replace('\u2066', ' ')\
    .replace('\u2069', ' ').replace('\u200b', ' ').replace('\u200d', ' ')\
    .replace('(click to view)', ' ')\
    .replace('a post shared by', ' ')\
    .replace('app users click here', ' ')\
    .replace('app users: click here', ' ')\
    .replace('app users, click here:', ' ')\
    .replace('click here.', ' ')\
    .replace('click here for more cartoons', ' ')\
    .replace('click here for more', ' ')\
    .replace('click here for more sports coverage on foxnews.com', ' ')\
    .replace('click here for other fox news digital adoptable pets stories', ' ')\
    .replace('click here for the fox news app', ' ')\
    .replace('click here for the latest fox news reporting', ' ')\
    .replace('click here for topline and cross tabs conducted', ' ')\
    .replace('click here to hear more', ' ')\
    .replace('click here to ge the fox news app', ' ')\
    .replace('click here to get the fox news app', ' ')\
    .replace('click here to get the opinion newsletter', ' ')\
    .replace('click here to learn more', ' ')\
    .replace('click here to read more', ' ')\
    .replace('click here to sign up for our health newsletter', ' ')\
    .replace('click here to sign up for our lifestyle newsletter', ' ')\
    .replace('click here to sign up for our opinion newsletter', ' ')\
    .replace('click here to sign up for the entertainment newsletter', ' ')\
    .replace('click here to subscribe and get your first year of fox nation free of charge', ' ')\
```

```
    .replace('click here to view', ' ')\
    .replace("click to get kurt's cyberguy newsletter with quick tips, tech reviews, security alerts and ea
    .replace("click to get kurt's cyberguy newsletter with security alerts, quick tips, tech reviews, secur
    .replace("click to get kurt's free cyberguy newsletter with quick tips, tech reviews, security alerts a
    .replace("click to get kurt's free cyberguy newsletter with security alerts, quick tips, tech reviews,
    .replace('click to get the fox news app', ' ')\
    .replace('fox news digital', ' ')\
    .replace('request for comment', ' ')\
    .replace('the ap ', ' ')\
    .replace('copyright © 2023 breitbart', ' ')\
    .replace('all rights reserved', ' ')\
    .replace('copyright 2023 cyberguy.com', ' ')\
    .replace('copyright 2023 fox news network', ' ')\
    .replace('copyright 2023 viq media transcription', ' ')\
    .replace("please let us know if you're having issues with commenting", ' ')\
    .replace('view this post on instagram', ' ')
    #txt = txt
    #text = text.replace(r'200b', 'd171c')
    #text = rex_ucode.sub('', text)
    return text

def normalize(text):
    text = tprep.normalize.hyphenated_words(text)
    text = tprep.normalize.quotation_marks(text)
    text = tprep.normalize.unicode(text)
    text = tprep.remove.accents(text)
    return text
```

LEMMATIZATION FUNCTION

In [212…

```
nlp_trans = spacy.load('en_core_web_sm')

def lemma(text):
    trans_txt = nlp_trans(text)
    tokens = [t.lemma_ for t in trans_txt]
    return tokens
```

- CASE LOAD
- STOPWORD REMOVAL
- URL REMOVAL
- EMOJI REMOVAL
- PUNCTUATION REMOVAL
- MESSY TEXT REMOVAL
- TOKENIZE

In [217…

```
# CASE LOAD, REMOVE STOPWORDS,
# EMOJI and PUNCTUATION REMAL,
# URL REMOVAL
# TOKENIZE
# REMOVE MESSY text

punctuation = set(punctuation) # speeds up comparison
tw_punct = punctuation - {"#"}

sw = stopwords.words("english")
sw = sw + ['nan']
sw = sw + ['said'] + ['news'] + ['us'] + ['reuters'] + ['ap'] \
    + ['fox'] + ['cnn'] + ['breitbart'] + ['digital'] + ['follow'] \
    + ['associated press'] + ['press contributed'] + ['press'] \
    + ['dont'] + ['2023'] + ['told digital'] + ['associated contributed']\
    + ['contributed report'] + ['associated'] + ['contributed'] +\
    ['report'] + ['continued'] + ['reportedly'] + ['im']

# Two useful regex
whitespace_pattern = re.compile(r"\s+")
hashtag_pattern = re.compile(r"^#[0-9a-zA-Z]+")

def emoji_split(text):
    return("".join([' ' + ch + ' ' if emoji.is_emoji(ch) else ch for ch in text]))

def remove_stop(tokens) :
```

```
    # modify this function to remove stopwords

    return[t for t in tokens if t not in sw]

def remove_punctuation(text, punct_set=tw_punct) :
    return("".join([ch for ch in text if ch not in punct_set]))

def tokenize(text) :
    """ Splitting on whitespace rather than the book's tokenize function. That
        function will drop tokens like '#hashtag' or '2A', which we need for Twitter. """

    return([item.lower() for item in whitespace_pattern.split(text)])

def remove_url(text):
    return(re.sub(r'http\S+', '', text))

def remove_messy(text): # remove words that give away the source
    text1=re.sub(r'cnn', '', text)
    text2=re.sub(r'fox', '', text1)
    text3=re.sub(r' — ', '', text2)
    text4=re.sub(r'breitbart', '', text3)
    return(re.sub(r'\\n', '', text4))

# two pipelines to either tokenize or simply remove punctuation
# and lowercase as we will need to extract feature words:

full_pipeline = [str.lower, remove_url, rex_replace, emoji_split, remove_messy,
                 remove_punctuation, tokenize, remove_stop]
first_pipeline = [str.lower, remove_url, rex_replace, emoji_split, remove_messy,
                  remove_punctuation]


def prepare(text, pipeline) :
    tokens = str(text)

    for transform in pipeline :
        tokens = transform(tokens)

    return(tokens)
```

Feature extraction Function:

In [7]:

```
def conv_features(text,fw) :
     feature_set=dict()
     for word in text.split():
          if word in fw:
               feature_set[word]=True
     return(feature_set)
```

EDA functions:

- GET PATTERNS
- WORD COUNTS
- WORDCLOUD
- TOPIC MODELING

In [8]:

```
def get_patterns(text_analyze, num_words, T):
    if(len(text_analyze)==0):
        raise ValueError("Can't work with empty text object")
    total_tokens = 1
    unique_tokens = 0
    avg_token_len = 0.0
    lexical_diversityP = 0.0
    top_words = []

    # Only applying the token_normal, which takes only alphanumeric values
    # to twitter data:
    if T ==1:
        text_analyze=token_normal(text_analyze)

    total_tokens = len(text_analyze)
```

```python
    unique_tokens = len(set(text_analyze))
    lexical_diversityP = unique_tokens/total_tokens
    avg_token_len = np.mean([len(ta) for ta in text_analyze])

    top_words_1 = collections.Counter(text_analyze)
    top_words = top_words_1.most_common(num_words)

    results={'tokens': total_tokens,
             'unique_tokens': unique_tokens,
             'avg_token_length': avg_token_len,
             'lexical_diversity': lexical_diversityP,
             'top_words': top_words}
    return(results)
```

In [9]:

```python
def wordcloud(word_freq, title=None, max_words=200, stopwords=None):

    wc = WordCloud(width=800, height=400,
                   background_color= "black", colormap="Paired",
                   max_font_size=150, max_words=max_words)

    # convert data frame into dict
    if type(word_freq) == pd.Series:
        counter = Counter(word_freq.fillna(0).to_dict())
    else:
        counter = word_freq

    # filter stop words in frequency counter
    if stopwords is not None:

        counter = {token:freq for (token, freq) in counter.items()
                              if token not in stopwords}
    wc.generate_from_frequencies(counter)

    plt.title(title)

    plt.imshow(wc, interpolation='bilinear')
    plt.axis("off")

# Here, we only apply splitting to the lyrics data due to the difference
# in dataframe/data ingestion between twitter and lycis data:

#def count_words(df, column='tokens', preprocess=None, min_freq=2, split=0):
def count_words(x, preprocess=None, min_freq=2, split=0):

    # process tokens and update counter
    def update(doc):
        tokens = doc if preprocess is None else preprocess(doc)
        counter.update(tokens)

    # create counter and run through all data
    #counter = collections.Counter()
    #top_words_1 = collections.Counter(text_analyze)
    #top_words = top_words_1.most_common(num_words)
    if split == 0:
        counter = collections.Counter(x)
    else:
        counter = collections.Counter(x.split())

    #df[column].map(update)

    # transform counter into data frame
    freq_df = pd.DataFrame.from_dict(counter, orient='index', columns=['freq'])
    freq_df = freq_df.query('freq >= @min_freq')
    freq_df.index.name = 'token'

    return freq_df.sort_values('freq', ascending=False)
```

In [10]:

```python
def display_topics(model, features, no_top_words=5):
    for topic, words in enumerate(model.components_):
        total = words.sum()
        largest = words.argsort()[::-1] # invert sort order
        print("\nTopic %02d" % topic)
        for i in range(0, no_top_words):
```

```
        print("  %s (%2.2f)" % (features[largest[i]],
                               abs(words[largest[i]]*100.0/total)))
```

Load Data from CSV's:

Full Dataset compiled for Training/Test of Classifier

- From CNN, Breitbart, Fox, and Washington Post:

In [154...
```
api_data_complete_df=pd.read_csv('../data/master.csv')
```

Client Dataset to collect Classifier Results for Client

- From The Hill: (already tokenized)

In [13]:
```
api_data_complete_df_business=pd.read_csv('master_business_TheHill.csv')
```

combining articles into one (no need to run again)

In [ ]:
```
api_data_complete_df=pd.read_csv('News_API_TheHill_wordcount3.csv')
api_data_complete_df.rename (columns = {'article_parsed':'article_text'}, inplace=True)
```

In [364...
```
api_data_complete_df_og=pd.read_csv('News_API_TheHill_wordcount.csv')
api_data_complete_df3=pd.read_csv('News_API_TheHill_wordcount3.csv')
Business_frames = [api_data_complete_df_og, api_data_complete_df3]

api_data_complete_df = pd.concat(Business_frames)
api_data_complete_df.rename (columns = {'article_parsed':'article_text'}, inplace=True)
```

In [366...
```
api_data_complete_df.head()
```

Out[366...

	Unnamed: 0	Source	Author	Title	URL	date	content	article_text
0	0	The Hill	Zach Schonfeld	Ketanji Brown Jackson issues solo dissent in r...	https://thehill.com/regulation/court-battles/4...	2023-06-01T15:38:33Z	Skip to content\r\nLiberal Justice Ketanji Bro...	\n\nLiberal Justice Ketanji Brown Jackson issu...
1	1	The Hill	Brett Samuels	How Biden pulled it off...	https://thehill.com/homenews/administration/40...	2023-06-01T06:31:36Z	Skip to content\r\nIn late March, the prospect...	\n\nIn late March, the prospects of President ...
2	2	The Hill	the hill	How Christie could be wildcard in 2024 race...	https://thehill.com/homenews/campaign/4029170-...	2023-06-01T12:00:04Z	The Memo: How Chris Christie could be a wildca...	\n\nFormer New Jersey Gov. Chris Christie is v...
3	3	The Hill	Alexander Bolton	Schumer announces agreement to pass debt ceili...	https://thehill.com/homenews/senate/4031054-sc...	2023-06-01T23:42:11Z	Senate Majority Leader Chuck Schumer (D-N.Y.) ...	\n\nSenate Majority Leader Chuck Schumer (D-N....
4	4	The Hill	Zack Budryk	Kaine introduces amendment to strip Manchin-ba...	https://thehill.com/policy/energy-environment/...	2023-06-01T16:43:29Z	Sen. Tim Kaine (D-Va.) added an amendment to t...	\n\nSen. Tim Kaine (D-Va.) added an amendment ...

In [365...

```
api_data_complete_df.shape
```

Out[365…
```
(181, 9)
```

Pre-Process Data:

(same process done to MASTER and THE_HILL_MASTER):

CHOOSE 1:

Business Data (The Hill)

In [354…
```
# If Business data loaded - this data is already
# tokenized, so no need to pre-process:

#api_data_complete_df=api_data_complete_df_business.copy()
```

Train/Test master Data (CNN, Fox, Breitbart, Washington Post)

In [155…
```
# Train/Test data loaded:
api_data_complete_df=api_data_complete_df.copy()
```

TOKENIZE COLUMN added:

In [218…
```
# Tokenize text:

api_data_complete_df['tokens']= api_data_complete_df['article_text'].apply(prepare,
                                                     pipeline=full_pipeline)
```

In [241…
```
api_data_complete_df_business['tokens']= api_data_complete_df_business['article_text'].apply(prepare,
                                                     pipeline=full_pipeline)
```

CLEAN DATA (without tokenizing) COLUMN added:

In [177…
```
# Clean data into lowercase/no punctuation:

api_data_complete_df['cleaner_text']= api_data_complete_df['article_text'].apply(prepare,
                                                     pipeline=first_pipeline)
```

In [242…
```
api_data_complete_df_business['cleaner_text']= api_data_complete_df_business['article_text'].apply(prepare,
                                                     pipeline=first_pipeline)
```

In [158…
```
# These results change depending on the data loaded that is being worked on:

api_data_complete_df.shape
```

Out[158…
```
(4509, 9)
```

If TRAIN data used: LABEL target variable:

In [159…
```
# Add target variable values:

api_data_complete_df['Political_Lean'] = np.where((api_data_complete_df['source_name'] == "CNN") | \
                                                   (api_data_complete_df['source_name'] == \
                                                    "The Washington Post"), 'Left', 'Right')
```

Saving new MASTER CSV;s (tokenized/labeled/etc) for the Business and training datasets

In [369…
```
#api_data_complete_df.to_csv("master_business_TheHill.csv", sep=',')
```

EDA

Add Word Counts Columns:

In [363…

```
api_data_complete_df=pd.read_csv('master_tokenized_labeled_af.csv')
```

In [153…

```
api_data_complete_df.head()
```

Out[153…

	source_name	author	title	url	publish_date	content	article_
0	The Washington Post	NaN	Alabama Highway sign hacked with white suprema...	https://www.washingtonpost.com/nation/2023/05/...	2023-05-30T16:31:36Z	Travelers in Alabama driving on Interstate 65 ...	Travele Alab drivin Inter
1	The Washington Post	Amber Phillips	Breaking down the GOP investigation into the B...	https://www.washingtonpost.com/politics/2023/0...	2023-05-30T19:56:33Z	Comment on this story\r\nComment\r\nA federal ...	A fe prose ma neari decis
2	The Washington Post	David Ovalle	Appeals court paves way for Purdue Pharma opio...	https://www.washingtonpost.com/health/2023/05/...	2023-05-30T23:52:34Z	Comment on this story\r\nComment\r\nA federal ...	A fe app c Tue cleared
3	The Washington Post	Philip Bump	Trump pledges to win an immigration fight he d...	https://www.washingtonpost.com/politics/2023/0...	2023-05-30T18:30:47Z	Comment on this story\r\nComment\r\nSpeaking i...	Speakii Orland Nover 2 Repul
5	The Washington Post	Paul Waldman	Why fear of change will drive the GOP presiden...	https://www.washingtonpost.com/opinions/2023/0...	2023-05-30T10:00:00Z	Comment on this story\r\nComment\r\nLook, we k...	"Lool know cour goi the w

In [178…

```
api_data_complete_df['word_count_tokens'] = api_data_complete_df['tokens'].apply(lambda x: \
                                                                     len(str(x).split(" ")))
#api_data_complete_df['word_count'] = api_data_complete_df['article_text'].apply(lambda x: len(str(x).split
```

In [179…

```
api_data_complete_df['word_count_cleaner'] = api_data_complete_df['cleaner_text'].apply(lambda x:\
                                                                              len(str(x).split("
```

In [180…

```
api_data_complete_df['word_count_tokens'].mean()
```

Out[180…

```
428.96517302573204
```

In [181…

```
api_data_complete_df = api_data_complete_df[api_data_complete_df['word_count_tokens']>1]
```

Remove "centered" authors from Training/Test Data:

In [182…

```
# Removing Reuters, ms, and Associated Press authors from data:

api_data_complete_df2 = api_data_complete_df[~api_data_complete_df['author'].isin(['msn', 'Associated Press

display(api_data_complete_df2.head())

display(api_data_complete_df2['Political_Lean'].value_counts())
```

	source_name	author	title	url	publish_date	content	article_
0	The Washington Post	NaN	Alabama Highway sign hacked with white suprema...	https://www.washingtonpost.com/nation/2023/05/...	2023-05-30T16:31:36Z	Travelers in Alabama driving on Interstate 65 ...	Travele Alab drivin Inter
1	The Washington Post	Amber Phillips	Breaking down the GOP investigation into the B...	https://www.washingtonpost.com/politics/2023/0...	2023-05-30T19:56:33Z	Comment on this story\r\nComment\r\nA federal ...	A fe prosec ma neari decis
2	The Washington Post	David Ovalle	Appeals court paves way for Purdue Pharma opio...	https://www.washingtonpost.com/health/2023/05/...	2023-05-30T23:52:34Z	Comment on this story\r\nComment\r\nA federal ...	A fe app (Tue cleare
3	The Washington Post	Philip Bump	Trump pledges to win an immigration fight he d...	https://www.washingtonpost.com/politics/2023/0...	2023-05-30T18:30:47Z	Comment on this story\r\nComment\r\nSpeaking i...	Speaki Orlanc Nover 2 Repul
5	The Washington Post	Paul Waldman	Why fear of change will drive the GOP presiden...	https://www.washingtonpost.com/opinions/2023/0...	2023-05-30T10:00:00Z	Comment on this story\r\nComment\r\nLook, we k...	"Lool know cour goi the w

```
Political_Lean
Right     2758
Left      1268
Name: count, dtype: int64
```

In [183...

```
api_data_complete_df2.to_csv("master_tokenized_labeled_af.csv", sep=',')
```

Word Clouds

In [366...

```
# Separate Left and Right Lean articles to analyze as groups:

Left_lean_articles_df=api_data_complete_df2[api_data_complete_df2['Political_Lean']=="Left"]
Right_lean_articles_df=api_data_complete_df2[api_data_complete_df2['Political_Lean']=="Right"]
```

In [367...

```
# Generate list from Left an Right dataframes:

Left_text=[token for sublist in
           Left_lean_articles_df['tokens']
           for token in sublist]
Right_text=[token for sublist in
            Right_lean_articles_df['tokens']
            for token in sublist]
```

In [195...

```
#Left_text
```

In [15]:

```
# Left lean vs Right lean word clouds:

Left_Lean_counts = collections.Counter(Left_text)


Right_Lean_counts = collections.Counter(Right_text)



print("\nLeft Leaning Article's top 5 words:\n")
for HT, count in Left_Lean_counts.most_common(5):
    print(f"{HT}: {count}")
```

```python
print("\nRight Leaning Article's top 5 words:\n")
for HT, count in Right_Lean_counts.most_common(5):
    print(f"{HT}: {count}")
```

```
Left Leaning Article's top 5 words:

would: 3591
trump: 3442
also: 2774
house: 2566
people: 2507

Right Leaning Article's top 5 words:

biden: 4453
president: 3767
also: 3621
would: 3512
people: 3375
```

In [18]:

```python
Left_Lean_counts = count_words(Left_text, split=0)
Right_Lean_counts = count_words(Right_text, split=0)
display(Left_Lean_counts)
```

	freq
token	
would	3591
trump	3442
also	2774
house	2566
people	2507
...	...
paints	2
houghton	2
912	2
k5	2
andreeva	2

27475 rows × 1 columns

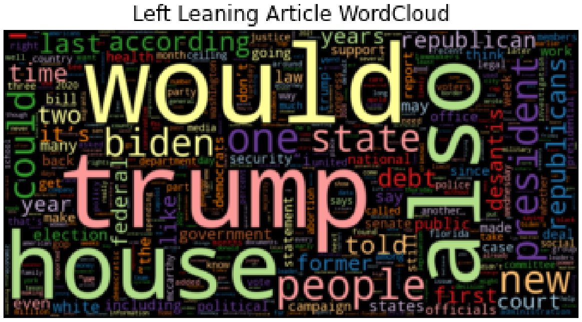
In [ ]:

```python
#her_df=lyrics_data_df.loc[0,:]
#robyn_df=lyrics_data_df.loc[1,:]
```

In [19]:

```python
wordcloud(Left_Lean_counts['freq'], title="Left Leaning Article WordCloud", max_words=500)
```

Left Leaning Article WordCloud



In [20]:

```python
wordcloud(Right_Lean_counts['freq'], title="Right Leaning Article WordCloud", max_words=500)
```

Right Leaning Article WordCloud

Word Clouds reveal that both Left and Right leaning articles tend to have a high word count for their opposition; Left focusing on Trump while the Right focuses on the current president Biden.

Topic Modeling NMF:

In [39]:
```
Left_tfidf_topic = TfidfVectorizer(stop_words=list(sw), min_df=5, max_df=0.7, ngram_range=(1,2))
Left_topic_modeling_input = Left_tfidf_topic.fit_transform(Left_lean_articles_df['cleaner_text'])
```

In [40]:
```
Right_tfidf_topic = TfidfVectorizer(stop_words=list(sw), min_df=5, max_df=0.7, ngram_range=(1,2))
Right_topic_modeling_input = Right_tfidf_topic.fit_transform(Right_lean_articles_df['cleaner_text'])
```

In [49]:
```
nmf_text_model_newsL = NMF(n_components=3, random_state=314)
Left_text_matrix = nmf_text_model_newsL.fit_transform(Left_topic_modeling_input)
HLeft_text_matrix = nmf_text_model_newsL.components_
```

In [50]:
```
nmf_text_model_newsR = NMF(n_components=3, random_state=314)
Right_text_matrix = nmf_text_model_newsR.fit_transform(Right_topic_modeling_input)
HRight_text_matrix = nmf_text_model_newsR.components_
```

Display Topics for Left vs Right:

In [51]:
```
display_topics(nmf_text_model_newsL, Left_tfidf_topic.get_feature_names_out())
```

```
Topic 00
  trump (1.75)
  desantis (1.14)
  president (0.32)
  campaign (0.32)
  former (0.31)

Topic 01
  debt (0.97)
  house (0.63)
  mccarthy (0.61)
  biden (0.60)
  debt ceiling (0.57)

Topic 02
  court (0.21)
  state (0.21)
  police (0.15)
  people (0.15)
  abortion (0.14)
```

In [52]:
```
display_topics(nmf_text_model_newsR, Right_tfidf_topic.get_feature_names_out())
```

```
Topic 00
  biden (0.22)
  debt (0.17)
  house (0.16)
  ai (0.14)
  bill (0.13)

Topic 01
  border (1.72)
  migrants (1.12)
```

```
  title (0.71)
  title 42 (0.65)
  42 (0.64)

Topic 02
  desantis (1.29)
  trump (1.24)
  percent (0.59)
  president (0.41)
  florida (0.39)
```

Topic Modeling using NMF reveals that the top three topics depending on political lean are:

Left:

- Trump/Desantis relationship
- US debt ceiling
- Abortion Laws

Right:

- Bills to change Bill of Rights and regulate AI
- Title 42/Migrants
- Relationship DeSantis and Trump

LDA topic modeling for visualization:

In [368...

```
Lcount_text_vectorizer = CountVectorizer(stop_words=list(sw), min_df=5, max_df=0.7)
Left_count_text_vectors = Lcount_text_vectorizer.fit_transform(Left_lean_articles_df['cleaner_text'])
Left_count_text_vectors.shape

Rcount_text_vectorizer = CountVectorizer(stop_words=list(sw), min_df=5, max_df=0.7)
Right_count_text_vectors = Rcount_text_vectorizer.fit_transform(Right_lean_articles_df['cleaner_text'])
Right_count_text_vectors.shape
```

Out[368...

```
(2758, 13356)
```

In [376...

```
Left_lda_para_model = LatentDirichletAllocation(n_components = 3, random_state=42)
W_lda_para_matrix_Left = Left_lda_para_model.fit_transform(Left_count_text_vectors)
H_lda_para_matrix_Left = Left_lda_para_model.components_
```

In [377...

```
Right_lda_para_model = LatentDirichletAllocation(n_components = 3, random_state=42)
W_lda_para_matrix_Right = Right_lda_para_model.fit_transform(Right_count_text_vectors)
H_lda_para_matrix_Right = Right_lda_para_model.components_
```

In [378...

```
display_topics(Left_lda_para_model, Lcount_text_vectorizer.get_feature_names_out())
```

```
Topic 00
  trump (1.59)
  people (0.49)
  election (0.45)
  president (0.44)
  former (0.38)

Topic 01
  state (0.69)
  people (0.57)
  health (0.44)
  new (0.42)
  abortion (0.39)

Topic 02
  biden (1.01)
  house (0.98)
  republicans (0.67)
```

```
  debt (0.67)
  president (0.55)
```

In [379…

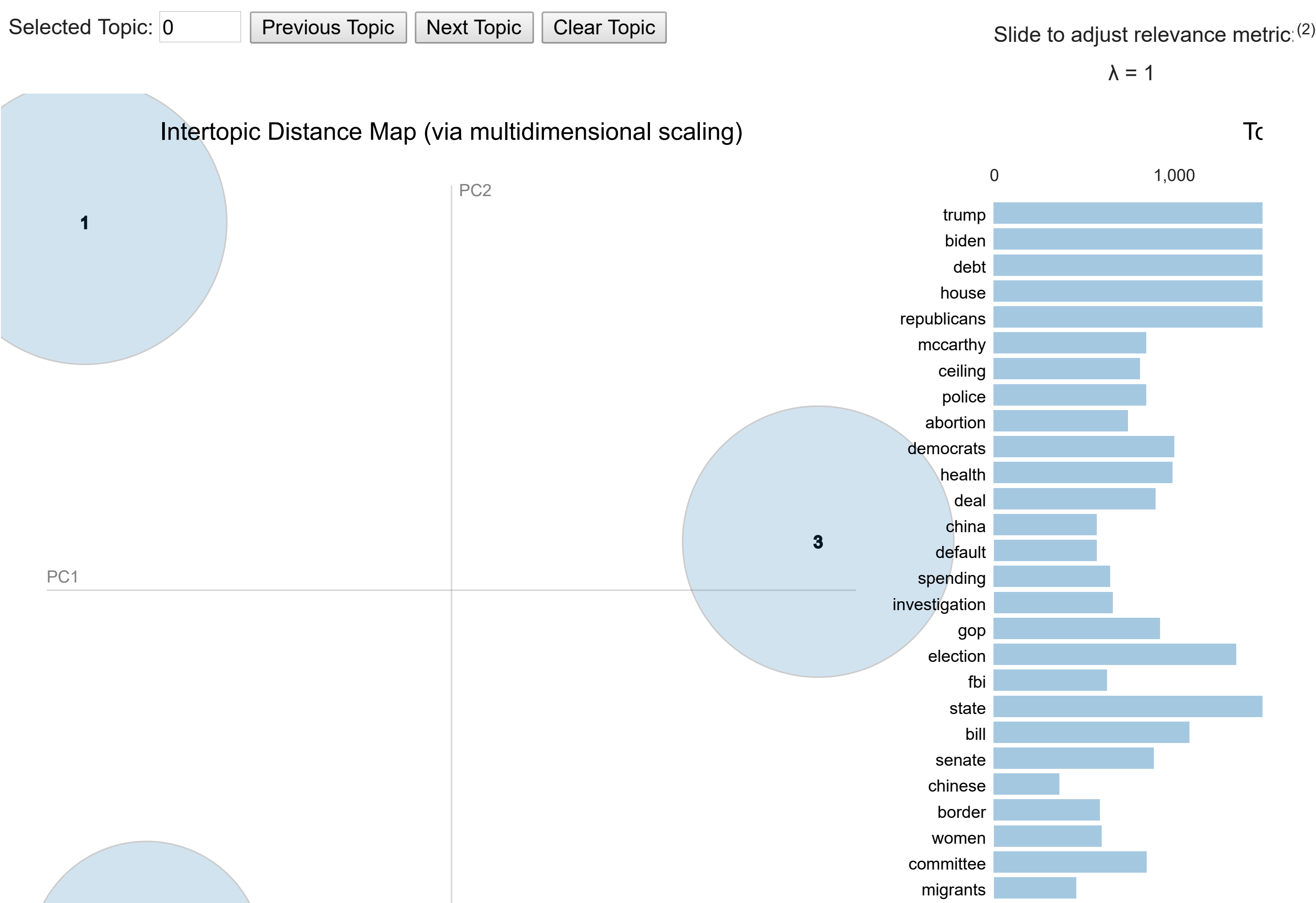
```
display_topics(Right_lda_para_model, Rcount_text_vectorizer.get_feature_names_out())
```

```
Topic 00
  police (0.46)
  people (0.39)
  also (0.38)
  ai (0.36)
  one (0.35)

Topic 01
  trump (1.05)
  desantis (0.65)
  president (0.50)
  former (0.50)
  also (0.41)

Topic 02
  biden (1.78)
  border (0.94)
  house (0.88)
  president (0.80)
  would (0.53)
```

In [380…

```
lda_display_left = pyLDAvis.lda_model.prepare(Left_lda_para_model, Left_count_text_vectors,
                                              Lcount_text_vectorizer, sort_topics=False)
pyLDAvis.display(lda_display_left)
```

Out[380…



In [381…

```
pyLDAvis.save_html(lda_display_left, 'lda_left.html')
```

In [382…

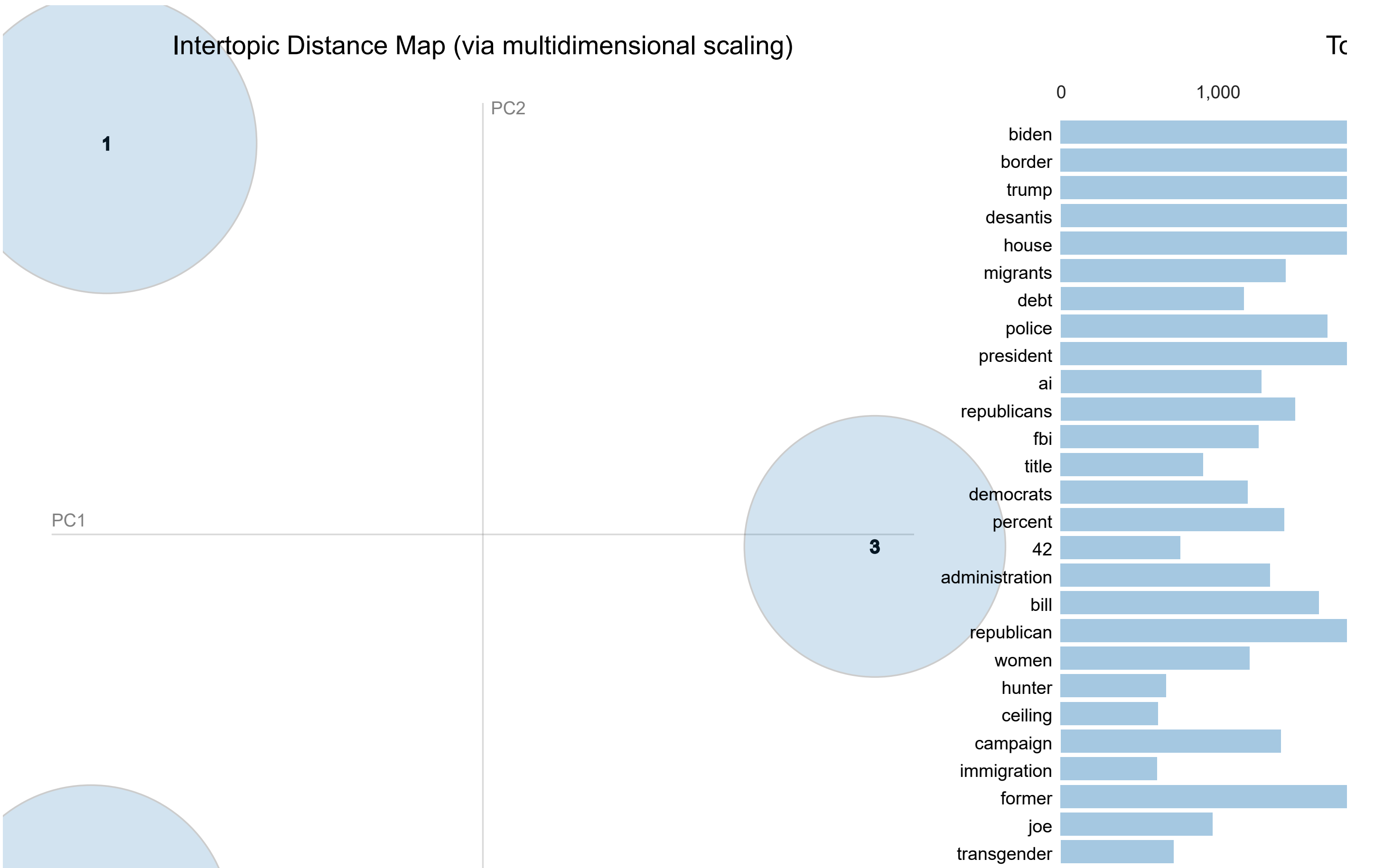
```
lda_display_right = pyLDAvis.lda_model.prepare(Right_lda_para_model, Right_count_text_vectors,
                                               Rcount_text_vectorizer, sort_topics=False)
pyLDAvis.display(lda_display_right)
```

Out[382…

Selected Topic: 0 | Previous Topic | Next Topic | Clear Topic

Slide to adjust relevance metric:(2)

λ = 1



In [383…

```
pyLDAvis.save_html(lda_display_right, 'lda_right.html')
```

Topic Modeling using LDA reveals that the top three topics depending on political lean are:

Left:

- Healthcare
- McCarthy/Biden Debt Ceiling
- Trump/DeSantis relationship
- Justice system, police

Right:

- Unclear/school-related (the visualization shows this topic overlaps with the following one a bit)
- President, Biden, Trump, politics
- Justice system, fbi
- Immigration

Missing Values:

Only one missing value for training data:

In [223…

```
#api_data_complete_df2.isna().sum()
```

Modeling:

In [57]:
```
# Obtain total counts of words in the entire corpus:

word_dist=Counter([item for sublist in api_data_complete_df['tokens']
                   for item in sublist])
```

Prepare data for modeling (Target defined, clean text as X)

In [46]:
```
# generate the dict data to then be filtered through
# the filtered_words list:

news_data=dict()


news_data=[(api_data_complete_df2.at[index,'cleaner_text'],
            api_data_complete_df2.at[index,'Political_Lean']) \
           for (index,row) in api_data_complete_df2.iterrows()]
```

Feature Words filtering:

In [47]:
```
word_cutoff=5
feature_words2=[]
for word, count in word_dist.items() :
    #for convention_data_df['word_dist']
    if count > word_cutoff :
        feature_words2.append(word)

print(f"With a word cutoff of {word_cutoff}, we have {len(feature_words2)} as features in the model.")
```

```
With a word cutoff of 5, we have 22181 as features in the model.
```

In [48]:
```
# Filter the data through the feature words set
# determined above:

featuresets=dict()
featuresets = [(conv_features(text,feature_words2),
                lean) for (text, lean) in news_data]
```

Rough Naive-Bayes Classifier setup and run-through:

In [49]:
```
random.seed(42)
random.shuffle(featuresets)
test_size = 20
```

In [50]:
```
test_set=dict()
train_set=dict()
test_set, train_set = featuresets[:test_size], featuresets[test_size:]
```

In [51]:
```
classifier = nltk.NaiveBayesClassifier.train(train_set)
print(nltk.classify.accuracy(classifier, test_set))
```

```
0.2
```

In [52]:
```
# Confusion Matrix:

predicted_labels = [classifier.classify(features) for features,
                    label in test_set]
gold_labels = [label for features, label in test_set]

cm = ConfusionMatrix(gold_labels, predicted_labels)
print(cm.pretty_format(sort_by_count=True, show_percents=True))
```

```
      |       R       |
      |       i     L |
      |       g     e |
      |       h     f |
      |       t     t |
------+---------------+
```

```
Right |     <.> 80.0% |
 Left |       . <20.0%>|
------+---------------+
(row = reference; col = test)
```

Linear SVC classifier:

Prepare Data for Linear SVC (SVM) implementation:

In [184…

```
X_train, X_test, Y_train, Y_test = train_test_split(api_data_complete_df2['cleaner_text'],
                                                    api_data_complete_df2['Political_Lean'],
                                                    test_size=0.2,
                                                    random_state=42,
                                                    stratify=api_data_complete_df2['Political_Lean'])


print('Size of Training Data ', X_train.shape[0])
print('Size of Test Data ', X_test.shape[0])
```

```
Size of Training Data  3220
Size of Test Data  806
```

In [185…

```
# TF-IDF Vectorization for Training/Test Data:

tfidf = TfidfVectorizer(min_df = 10, max_df=0.7, ngram_range=(1,2), stop_words=sw)
X_train_tf = tfidf.fit_transform(X_train)
X_test_tf = tfidf.transform(X_test)
```

Hyperparameter tuning:

In [361…

```
parameters = {'C':[0.1, 1, 6, 6.5, 8], 'penalty':['l1', 'l2'], 'tol':[0.0000001,
                                                                     0.00001, 0.0001, 0.001, 0.01]}

svc_grid = LinearSVC(random_state=0)
clf_grid = GridSearchCV(svc_grid, parameters)
clf_grid.fit(X_train_tf, Y_train)
```

Out[361…

```
▸      GridSearchCV
▸ estimator: LinearSVC
      ▸ LinearSVC
```

In [362…

```
clf_grid.best_params_
```

Out[362…

```
{'C': 6, 'penalty': 'l2', 'tol': 1e-07}
```

The hyperparameter that gave the best results was tolerance at 1e-07, the others brought accuracy down so eliminated them

Train and Test Linear SVC model:

In [359…

```
# Train Lineary SVC Model with Training Data:

model1 = LinearSVC(random_state=0, tol=1e-7)
model1.fit(X_train_tf, Y_train)
```

Out[359…

```
▾              LinearSVC
LinearSVC(random_state=0, tol=1e-07)
```

In [389…

```
Y_train_pred = model1.predict(X_train_tf)

print ('Training Accuracy Score - ', accuracy_score(Y_train, Y_train_pred))
```

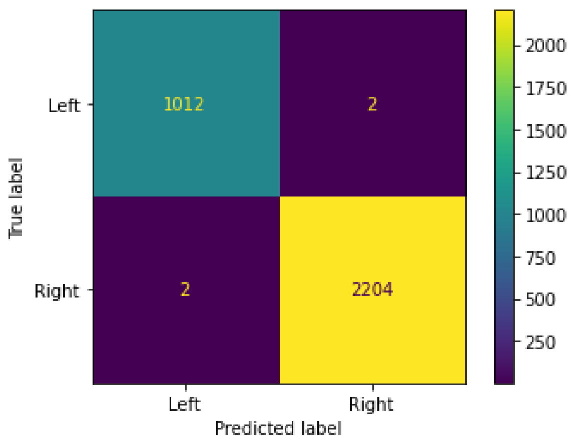
```
Training Accuracy Score -  0.9987577639751553
```

In [436…

```
train_svc_pred_cm = confusion_matrix(Y_train, Y_train_pred)
```

```
print(classification_report(Y_train, Y_train_pred))
print(train_svc_pred_cm)

train_svc_pred_cm_calc = ConfusionMatrixDisplay(confusion_matrix=train_svc_pred_cm,
                                                display_labels=model1.classes_)
train_svc_pred_cm_calc.plot()
plt.show()
```

```
              precision    recall  f1-score   support

        Left       1.00      1.00      1.00      1014
       Right       1.00      1.00      1.00      2206

    accuracy                           1.00      3220
   macro avg       1.00      1.00      1.00      3220
weighted avg       1.00      1.00      1.00      3220

[[1012    2]
 [   2 2204]]
```



Test Results Linear SVC:

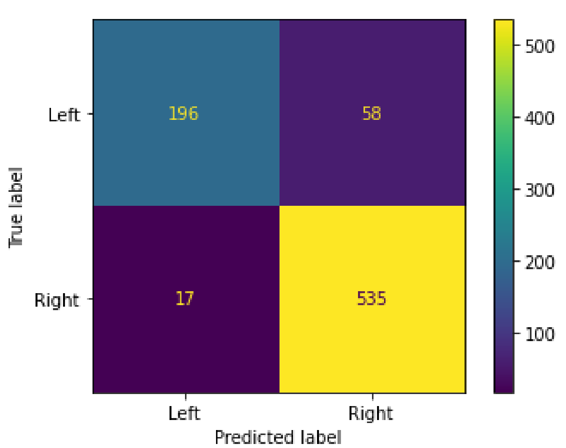
In [360…

```
Y_pred = model1.predict(X_test_tf)
print ('Accuracy Score - ', accuracy_score(Y_test, Y_pred))
#print ('F1 Score - ', recall_score(Y_test, Y_pred))
```

```
Accuracy Score -  0.9069478908188585
```

In [188…

```
Y_pred = model1.predict(X_test_tf)
confusion_matrix(Y_test, Y_pred)
cm = confusion_matrix(Y_test, Y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels = model1.classes_)
disp.plot()
plt.show()
```



In [189…

```
TNmodel1=cm[0][0]
FPmodel1=cm[0][1]
FNmodel1=cm[1][0]
TPmodel1=cm[1][1]
```

In [190…

```
# Results:

TANmodel1=TNmodel1+FPmodel1
TAPmodel1=TPmodel1+FNmodel1
TPPmodel1=FPmodel1+TPmodel1
TPNmodel1=TNmodel1+FNmodel1
GTmodel1=TANmodel1+TAPmodel1
AccuracyM1=(TNmodel1+TPmodel1)/GTmodel1
ErrorRateM1=1-AccuracyM1
SensitivityM1=TPmodel1/(TAPmodel1)
RecallM1=SensitivityM1
SpecificityM1=TNmodel1/TANmodel1
PrecisionM1=TPmodel1/TPPmodel1
F1M1=2*PrecisionM1*RecallM1/(PrecisionM1 + RecallM1)
F2M1=5*(PrecisionM1*RecallM1)/((4*PrecisionM1)+RecallM1)
Fp5M1=(1.25)*(PrecisionM1*RecallM1)/((0.25*PrecisionM1)+RecallM1)

header = ["Accuracy", "Error Rate", "Sensitivity", "Recall", "Specificity",
          "Precision", "F1", "F2", "F0.5"]
data1 = [["Accuracy", AccuracyM1], ["Error Rate", ErrorRateM1],
         ["Sensitivity", SensitivityM1],
         ["Recall", RecallM1], ["Specificity", SpecificityM1],
         ["Precision", PrecisionM1],
         ["F1", F1M1], ["F2", F2M1], ["F0.5", Fp5M1]]

col_names=["Measurement", "Linear SVC Model"]

ModelEvaluationTable = tabulate(data1, headers=col_names,
                                tablefmt="fancy_grid")

print(ModelEvaluationTable)
```

Measurement	Linear SVC Model
Accuracy	0.906948
Error Rate	0.0930521
Sensitivity	0.969203
Recall	0.969203
Specificity	0.771654
Precision	0.902192
F1	0.934498
F2	0.955016
F0.5	0.914843

In [299…

```
data1
```

Out[299…

```
[['Accuracy', 0.9069478908188585],
 ['Error Rate', 0.09305210918114148],
 ['Sensitivity', 0.9692028985507246],
 ['Recall', 0.9692028985507246],
 ['Specificity', 0.7716535433070866],
 ['Precision', 0.9021922428330523],
 ['F1', 0.9344978165938865],
 ['F2', 0.9550160656908249],
 ['F0.5', 0.91484268125855]]
```

In [303…

```
Data_metric_results_TheHill=pd.DataFrame(data1)
Data_metric_results_TheHill.head()
```

Out[303…

	0	1
0	Accuracy	0.906948
1	Error Rate	0.093052

	0	1
2	Sensitivity	0.969203
3	Recall	0.969203
4	Specificity	0.771654

In [304…

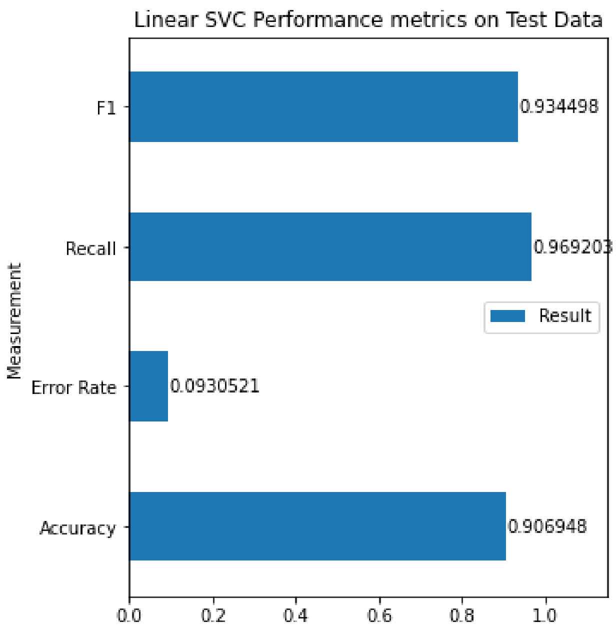
```
Data_metric_results_TheHill.rename (columns = {0:'Measurement'}, inplace=True)
Data_metric_results_TheHill.rename (columns = {1:'Result'}, inplace=True)
```

In [319…

```
#plt.bar(x=ModelEvaluationTable)


ax=Data_metric_results_TheHill[(Data_metric_results_TheHill['Measurement'] == 'Accuracy') |
                               (Data_metric_results_TheHill['Measurement'] == 'Recall') |
                               (Data_metric_results_TheHill['Measurement'] == 'F1') |
                               (Data_metric_results_TheHill['Measurement'] == \
                                'Error Rate')].plot(kind="barh",
                                                    x='Measurement',
                                     figsize=(5,6),
                                     title='Linear SVC Performance metrics on Test Data')
ax.bar_label(ax.containers[0])
ax.set_xlim(right=1.15)
```

Out[319…

```
(0.0, 1.15)
```



Because the classifier has a harder time classifying the Left class, our Accuracy is lower than Recall for the Right class. But still within acceptable range. F1 score is above .9 which was the goal. This classifier is good to try with the business case data give its speed and simpler design.

Save trained SVC model:

In [386…

```
# Path to save the pickled model
file_path = "model1_linSVC.pkl"

# Pickle the model
with open(file_path, "wb") as file:
    pickle.dump(model1, file)

print("Model pickled and saved successfully.")
```

```
Model pickled and saved successfully.
```

SKLEARN SVC Proba Model:

In [363…

```
svm = SVC(random_state=0, kernel='linear', probability=True)
```

```
svm.fit(X_train_tf, Y_train)
```

Out[363…

```
SVC
SVC(kernel='linear', probability=True, random_state=0)
```

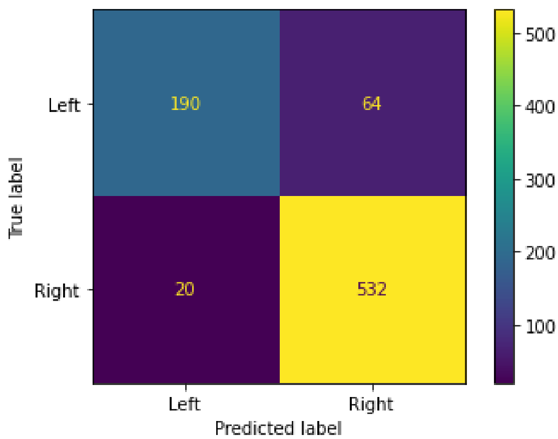
In [364…

```
Y_pred_sklearn = svm.predict(X_test_tf)
print ('Accuracy Score - ', accuracy_score(Y_test, Y_pred_sklearn))
```

```
Accuracy Score -  0.8957816377171216
```

In [203…

```
#confusion_matrix(Y_test, Y_pred_sklearn)
cm_sklearn = confusion_matrix(Y_test, Y_pred_sklearn)
disp_sklearn = ConfusionMatrixDisplay(confusion_matrix=cm_sklearn, display_labels = svm.classes_)
disp_sklearn.plot()
plt.show()
```



In [204…

```
SK_TNmodel1=cm_sklearn[0][0]
SK_FPmodel1=cm_sklearn[0][1]
SK_FNmodel1=cm_sklearn[1][0]
SK_TPmodel1=cm_sklearn[1][1]
```

In [205…

```
# Results:

SK_TANmodel1=SK_TNmodel1+SK_FPmodel1
SK_TAPmodel1=SK_TPmodel1+SK_FNmodel1
SK_TPPmodel1=SK_FPmodel1+SK_TPmodel1
SK_TPNmodel1=SK_TNmodel1+SK_FNmodel1
SK_GTmodel1=SK_TANmodel1+SK_TAPmodel1
SK_AccuracyM1=(SK_TNmodel1+SK_TPmodel1)/SK_GTmodel1
SK_ErrorRateM1=1-SK_AccuracyM1
SK_SensitivityM1=SK_TPmodel1/(SK_TAPmodel1)
SK_RecallM1=SK_SensitivityM1
SK_SpecificityM1=SK_TNmodel1/SK_TANmodel1
SK_PrecisionM1=SK_TPmodel1/SK_TPPmodel1
SK_F1M1=2*SK_PrecisionM1*SK_RecallM1/(SK_PrecisionM1 + SK_RecallM1)
SK_F2M1=5*(SK_PrecisionM1*SK_RecallM1)/((4*SK_PrecisionM1)+SK_RecallM1)
SK_Fp5M1=(1.25)*(SK_PrecisionM1*SK_RecallM1)/((0.25*SK_PrecisionM1)+SK_RecallM1)

header = ["Accuracy", "Error Rate", "Sensitivity", "Recall", "Specificity",
          "Precision", "F1", "F2", "F0.5"]
SK_data1 = [["Accuracy", SK_AccuracyM1], ["Error Rate", SK_ErrorRateM1],
         ["Sensitivity", SK_SensitivityM1],
         ["Recall", SK_RecallM1], ["Specificity", SK_SpecificityM1],
         ["Precision", SK_PrecisionM1],
         ["F1", SK_F1M1], ["F2", SK_F2M1], ["F0.5", SK_Fp5M1]]

col_names=["Measurement", "SKLEARN Linear SVC Model"]

SK_ModelEvaluationTable = tabulate(SK_data1, headers=col_names,
                                   tablefmt="fancy_grid")

print(SK_ModelEvaluationTable)
```

Measurement	SKLEARN Linear SVC Model
Accuracy	0.895782
Error Rate	0.104218
Sensitivity	0.963768
Recall	0.963768
Specificity	0.748031
Precision	0.892617
F1	0.926829
F2	0.948645
F0.5	0.905995

Features of Importance:

In [456…

```
# Get the most predictive words

feature_names = tfidf.get_feature_names_out()
#model1.coef_
top_words = sorted(zip(model1.coef_[0], feature_names), reverse=True)[:10]
#svm.coe
#top_words
```

In [457…

```
top_words_df=pd.DataFrame(top_words)

top_words_df.rename (columns = {0:'var_imp'}, inplace=True)
top_words_df.rename (columns = {1:'feature'}, inplace=True)
```

In [458…

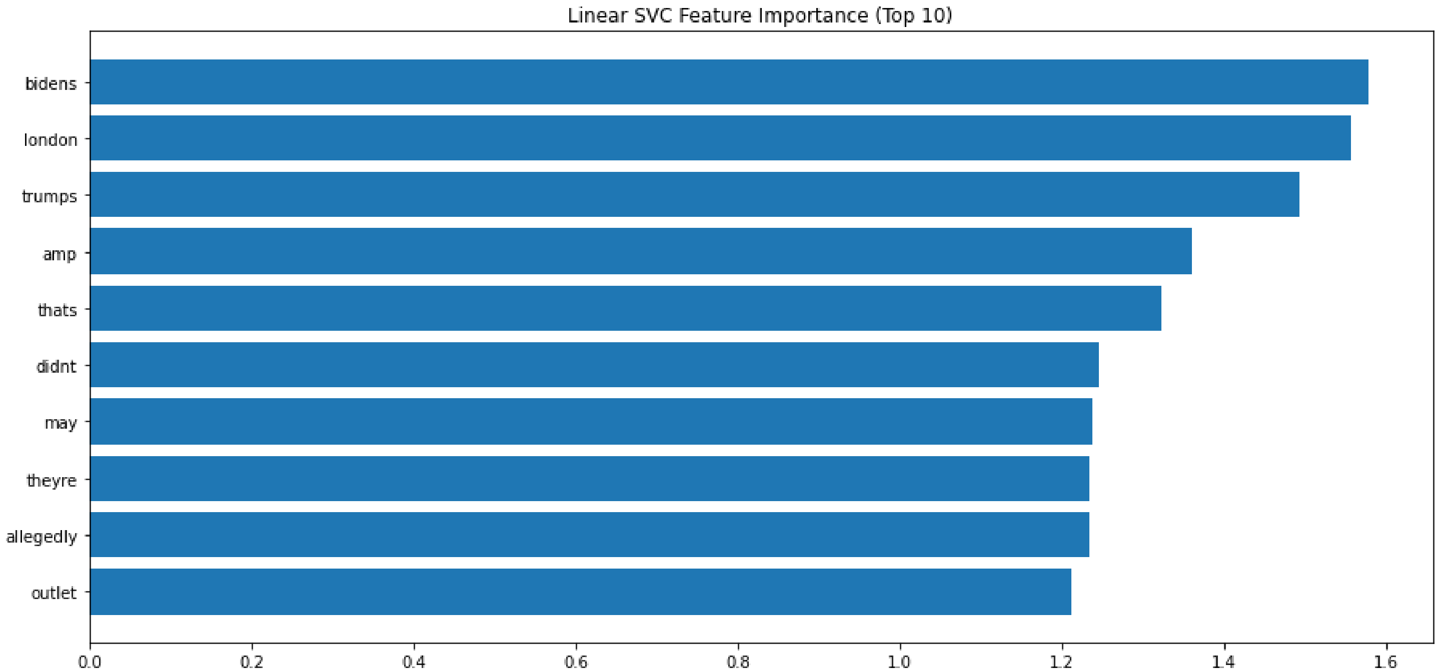
```
top_words_df.head()
```

Out[458…

	var_imp	feature
0	1.578366	bidens
1	1.556567	london
2	1.493616	trumps
3	1.359869	amp
4	1.322696	thats

In [460…

```
top_words_df.sort_values('var_imp',inplace=True)
plt.figure(figsize=(15,7))
plt.title('Linear SVC Feature Importance (Top 10)')
plt.barh([x for x in range(len(top_words_df['var_imp']))], top_words_df['var_imp'],
         tick_label=top_words_df['feature'])
plt.show()
```



These words are difficult to analyze without context. However, they help us know if there are any words that are indicative more of the journal/attributes of the news source that might give away the label instead of actual words in the articles that are relevant to political lean. We used this and found that certain phrases were indicating Fox News or other sources which might have helped drive accuracy deceptively high. This output helps us know that it is the text within articles that have helped classify the articles and develop our classifier.

Apply Classifier to Business Client Data:

In [243…

```
#Centered data Prep classification:

X_data = api_data_complete_df_business['cleaner_text']
```

In [244…

```
# TF-IDF Vectorization for Business application:

X_Data_Centered = tfidf.transform(X_data)
```

Linear SVD:

In [245…

```
Data_Classification_Centered = model1.predict(X_Data_Centered)
```

In [246…

```
print(api_data_complete_df_business['Author'])
```

```
0         Zach Schonfeld
1          Brett Samuels
2               the hill
3       Alexander Bolton
4            Zack Budryk
               ...
176         Tobias Burns
177        Julia Mueller
178       Caroline Vakil
179         Tobias Burns
180        Lauren Sforza
Name: Author, Length: 181, dtype: object
```

In [247…

```
Data_Classification_Centered
```

Out[247…

```
array(['Left', 'Left', 'Right', 'Right', 'Right', 'Right', 'Right',
       'Left', 'Left', 'Right', 'Left', 'Left', 'Right', 'Left', 'Left',
       'Left', 'Left', 'Right', 'Right', 'Right', 'Right', 'Left',
       'Right', 'Left', 'Left', 'Right', 'Left', 'Right', 'Right',
```

```
'Right', 'Left', 'Left', 'Right', 'Left', 'Left', 'Right', 'Left',
'Left', 'Right', 'Right', 'Left', 'Right', 'Left', 'Left', 'Left',
'Right', 'Right', 'Right', 'Left', 'Right', 'Left', 'Right',
'Right', 'Left', 'Left', 'Left', 'Right', 'Right', 'Left', 'Right',
'Left', 'Right', 'Right', 'Left', 'Right', 'Left', 'Right', 'Left',
'Left', 'Left', 'Right', 'Right', 'Left', 'Right', 'Left', 'Right',
'Right', 'Right', 'Right', 'Right', 'Right', 'Left', 'Right',
'Right', 'Left', 'Left', 'Left', 'Left', 'Right', 'Right', 'Left',
'Right', 'Right', 'Right', 'Right', 'Left', 'Left', 'Left',
'Right', 'Left', 'Left', 'Right', 'Left', 'Left', 'Left', 'Left',
'Left', 'Right', 'Left', 'Right', 'Right', 'Right', 'Left',
'Right', 'Left', 'Right', 'Left', 'Right', 'Left', 'Right', 'Left',
'Right', 'Left', 'Right', 'Left', 'Right', 'Right', 'Left',
'Right', 'Right', 'Right', 'Right', 'Right', 'Right', 'Right',
'Right', 'Right', 'Left', 'Left', 'Right', 'Left', 'Left', 'Left',
'Left', 'Right', 'Right', 'Right', 'Right', 'Right', 'Left',
'Right', 'Left', 'Right', 'Right', 'Right', 'Left', 'Right',
'Left', 'Left', 'Right', 'Right', 'Right', 'Left', 'Right',
'Right', 'Right', 'Left', 'Left', 'Right', 'Left', 'Left', 'Right',
'Right', 'Right', 'Left', 'Left', 'Right', 'Right', 'Right',
'Right', 'Right'], dtype=object)
```

In [248…

```python
left=0
right=0
for ii in range(0,len(Data_Classification_Centered)):
    if (Data_Classification_Centered[ii] == 'Left'):
        left=left+1
    elif (Data_Classification_Centered[ii] == 'Right'):
        right=right+1

print('Number of Left Articles: ', left, '\nNumber of Right Articles: ',
      right)
```

```
Number of Left Articles:  81
Number of Right Articles:  100
```

In [249…

```python
Data_centered_results=pd.DataFrame(Data_Classification_Centered)
```

In [250…

```python
Data_centered_results.rename (columns = {0:'Prediction'}, inplace=True)
```

In [251…

```python
Data_centered_results.head()
```

Out[251…

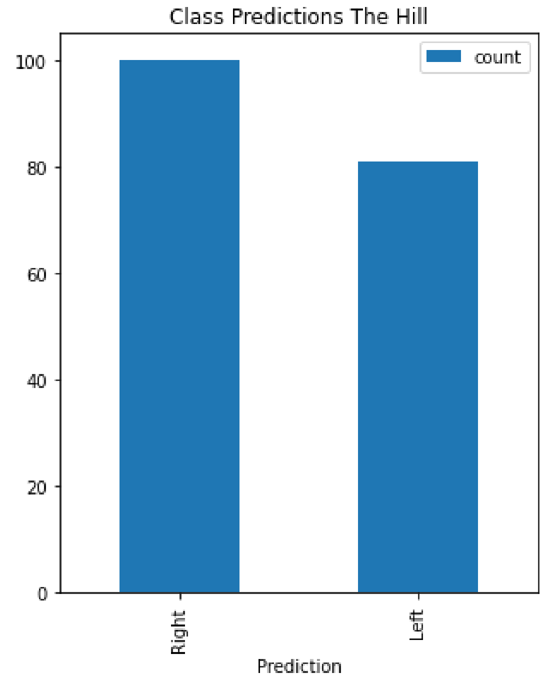
	Prediction
0	Left
1	Left
2	Right
3	Right
4	Right

In [252…

```python
Data_centered_results['Prediction'].value_counts().plot(kind="bar",
                                legend=True,
                                figsize=(5,6),
                                title='Class Predictions The Hill')
```

Out[252…

```
<AxesSubplot:title={'center':'Class Predictions The Hill'}, xlabel='Prediction'>
```



Even with a small dataset of 181 articles, we see almost an even distribution of Right and Left leaning classifications for The Hill. We are interested in seeing the confidence (probability ratings) for these classifications below.

SKLEARN SVC for probability testing:

In [253…
```
AP_predictions_proba = svm.predict_proba(X_Data_Centered)
```

In [254…
```
AP_predictions_proba[0][0]
```

Out[254…
```
0.9503953866731141
```

In [208…
```
len(AP_predictions_proba)
```

Out[208…
```
181
```

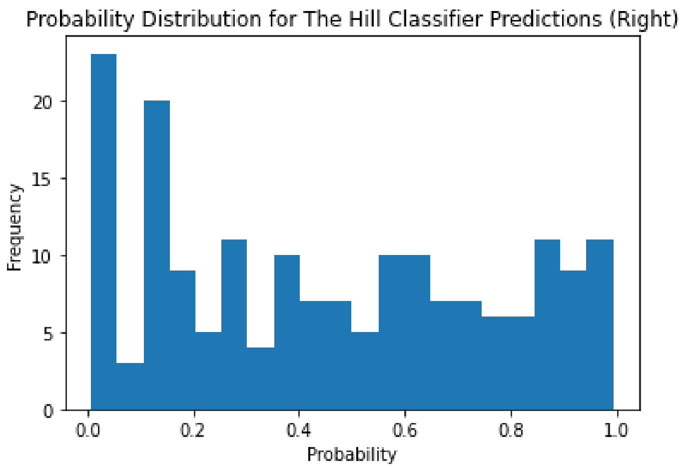
In [255…
```
#from sklearn.svm import SVC
#svm = SVC(kernel='linear', probability=True)
#svm.fit(X_train_tf, Y_train)

#AP_predictions_proba = svm.predict_proba(X_Data_Centered)

for pa in range(0,len(AP_predictions_proba)):
    for pa2 in range(0,1):
        if (AP_predictions_proba[pa][pa2] <= 0.65) & (AP_predictions_proba[pa][pa2] >= 0.5):
            print(pa, ':', AP_predictions_proba[pa][pa2], Data_Classification_Centered[pa])
```

```
2 : 0.5973377294016616 Right
5 : 0.505540954908968 Right
18 : 0.5137707984203023 Right
27 : 0.5645007945373783 Right
38 : 0.5801257602633187 Right
39 : 0.5756885039402224 Right
46 : 0.5418546159064842 Right
75 : 0.6216635081105005 Right
77 : 0.6216635081105005 Right
84 : 0.6413191667751802 Left
105 : 0.6412982042489684 Left
106 : 0.6412982042489684 Left
115 : 0.5 Right
119 : 0.5 Right
136 : 0.5857159103879271 Right
147 : 0.5893703782219359 Right
150 : 0.5547001230087428 Right
```

```
157 : 0.6448261346071565 Left
166 : 0.6448261346071565 Left
168 : 0.6242723322311122 Right
172 : 0.616816668944659 Right
175 : 0.611971953429539 Left
176 : 0.5 Right
179 : 0.5 Right
```

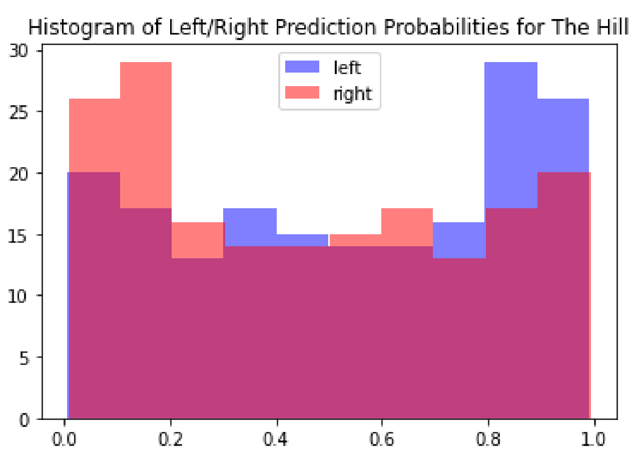
In [296…

```
#AP_predictions_proba

plt.hist(AP_predictions_proba[:, 1], bins=20)
plt.xlabel('Probability')
plt.ylabel('Frequency')
plt.title('Probability Distribution for The Hill Classifier Predictions (Right)')
plt.show()
```



In [481…

```
# Plotting histograms
plt.hist(AP_predictions_proba[:, 0], bins=10,
         alpha=0.5, color='blue', label='left')
plt.hist(AP_predictions_proba[:, 1], bins=10,
         alpha=0.5, color='red', label='right')

# Adding legend and title
plt.legend()
plt.title('Histogram of Left/Right Prediction Probabilities for The Hill')

# Displaying the plot
plt.show()
```



As we had hoped, The Hill appears to be much more balanced in their political lean, as is confirmed by the AllSides data. We did find a slight increase in Right leaning articles, but upon observation of the probability distribution, it is apparant that there are many low probability (low confidence) classifications for the lean. This distribution reveals that even when there is a lean classification, there is not an overwhelming number of confident classifications, which means The Hill is probably still a Centered online publication.

Apply Classifier to AP data:

Collect data saved in CSV and preprocess:

In [261…
```
api_data_complete_df_AP=pd.read_csv('News_API_AP_wordcount.csv')
```

In [262…
```
# Tokenize text:

api_data_complete_df_AP['tokens']= api_data_complete_df_AP['article_parsed'].apply(prepare,
                                                    pipeline=full_pipeline)
# Clean data into lowercase/no punctuation:

api_data_complete_df_AP['cleaner_text']= api_data_complete_df_AP['article_parsed'].apply(prepare,
                                                    pipeline=first_pipeline)
api_data_complete_df_AP['word_count_tokens'] = api_data_complete_df_AP['tokens'].apply(lambda x:\
                                                                                        len(str(x).\
                                                                                            split(" ")))

api_data_complete_df_AP = api_data_complete_df_AP[api_data_complete_df_AP['word_count_tokens']>1]

api_data_complete_df_AP.to_csv("master_tokenized_AP.csv", sep=',')
```

In [269…
```
#Centered data Prep classification:

X_data_AP = api_data_complete_df_AP['cleaner_text']
```

In [270…
```
# TF-IDF Vectorization for Business application:

X_Data_Centered_AP = tfidf.transform(X_data_AP)
```

Linear SVD:

In [271…
```
Data_Classification_Centered_AP = model1.predict(X_Data_Centered_AP)
```

In [273…
```
print(api_data_complete_df_AP['Author'])
```

```
0              By ALANNA DURKIN RICHER - Associated Press
1                       By SEUNG MIN KIM Associated Press
2                                         Bernard Condon
3       By KIMBERLEE KRUESI, SARAH RANKIN and DENISE L...
4                                     Brendan Farrington
                              ...
183     By LISA MASCARO, KEVIN FREKING and STEPHEN GRO...
184                  By FARNOUSH AMIRI - Associated Press
185               By RADUL RADOVANOVIC - Associated Press
186                  By FARNOUSH AMIRI - Associated Press
187     By LISA MASCARO, KEVIN FREKING and STEPHEN GRO...
Name: Author, Length: 188, dtype: object
```

In [274…
```
Data_Classification_Centered_AP
```

Out[274…
```
array(['Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Right',
       'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left',
       'Left', 'Right', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left',
       'Left', 'Left', 'Right', 'Left', 'Left', 'Left', 'Left', 'Left',
       'Left', 'Left', 'Left', 'Right', 'Left', 'Left', 'Left', 'Left',
       'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left',
       'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left',
       'Left', 'Left', 'Right', 'Left', 'Left', 'Left', 'Right', 'Right',
       'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left',
       'Left', 'Left', 'Left', 'Right', 'Left', 'Right', 'Left', 'Right',
       'Left', 'Left', 'Left', 'Right', 'Left', 'Left', 'Left', 'Left',
       'Left', 'Left', 'Left', 'Right', 'Left', 'Left', 'Left', 'Left',
       'Right', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left',
       'Left', 'Right', 'Left', 'Right', 'Left', 'Left', 'Left', 'Left',
       'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left',
       'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left',
       'Left', 'Left', 'Left', 'Left', 'Left', 'Right', 'Left', 'Left',
       'Left', 'Left', 'Left', 'Left', 'Right', 'Left', 'Left', 'Left',
```

```
       'Left', 'Left', 'Left', 'Right', 'Left', 'Left', 'Left', 'Left',
       'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left',
       'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left', 'Left',
       'Right', 'Right', 'Left', 'Right', 'Left', 'Left', 'Right', 'Left',
       'Left', 'Left', 'Left', 'Right', 'Left', 'Left', 'Right', 'Left',
       'Left', 'Left', 'Left', 'Left'], dtype=object)
```

In [275...

```
left=0
right=0
for ii in range(0,len(Data_Classification_Centered_AP)):
    if (Data_Classification_Centered_AP[ii] == 'Left'):
        left=left+1
    elif (Data_Classification_Centered_AP[ii] == 'Right'):
        right=right+1

print('Number of Left Articles: ', left, '\nNumber of Right Articles: ',
      right)
```

```
Number of Left Articles:  164
Number of Right Articles:  24
```

In [276...

```
Data_centered_results_AP=pd.DataFrame(Data_Classification_Centered_AP)
```

In [277...

```
Data_centered_results_AP.rename (columns = {0:'Prediction'}, inplace=True)
```

In [278...

```
Data_centered_results_AP.head()
```

Out[278...

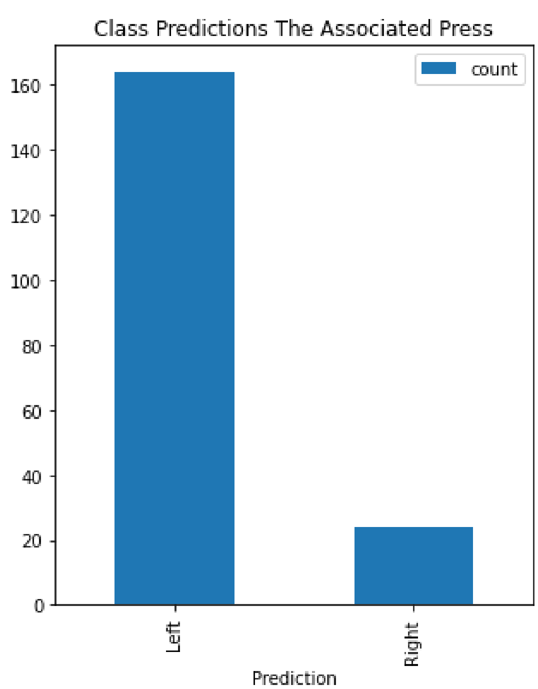
	Prediction
0	Left
1	Left
2	Left
3	Left
4	Left

In [279...

```
Data_centered_results_AP['Prediction'].value_counts().plot(kind="bar",
                                                  legend=True,
                                                  figsize=(5,6),
                                                  title='Class Predictions The Associated Press')
```

Out[279...

```
&lt;AxesSubplot:title={'center':'Class Predictions The Associated Press'}, xlabel='Prediction'&gt;
```



An overwhelming majority of Associated press articles were categorized as Left Leaning.

SKLEARN SVC for probability testing:

In [280…

```
AP_predictions_proba_AP = svm.predict_proba(X_Data_Centered_AP)
```

In [281…

```
AP_predictions_proba_AP[0][0]
```

Out[281…

```
0.9508323188246903
```

In [292…

```
AP_predictions_proba_AP[1][0]
```

Out[292…

```
0.981768860823333
```

In [294…

```
for x in range(0,len(AP_predictions_proba_AP)):
    print(AP_predictions_proba_AP[x][0])
    print(Data_Classification_Centered_AP[x])
```

```
0.9508323188246903
Left
0.981768860823333
Left
0.9614810136661492
Left
0.98661746903831
Left
0.891259423999621
Left
0.9906278481561918
Left
0.9427318115573183
Left
0.5336534447481074
Right
0.98661746903831
Left
0.936648044221054
Left
0.981768860823333
Left
0.9630019060086964
Left
0.6940622912199284
Left
0.803178366915479
Left
0.9508323188246903
Left
0.784522092358475
Left
0.9808996379009253
Left
0.26829051965364115
Right
0.9972611023492843
Left
0.9183765606311858
Left
0.9972611023492843
Left
0.9902424311393712
Left
0.9972611023492843
Left
0.9183765606311858
Left
0.8461805772804466
Left
0.9902424311393712
Left
```

0.08359528360983542
Right
0.9183765606311858
Left
0.7147570033831585
Left
0.7832130005086422
Left
0.7147570033831585
Left
0.9865357100592266
Left
0.7832130005086422
Left
0.7147570033831585
Left
0.9865357100592266
Left
0.278292939996084
Right
0.7096360056069901
Left
0.9611433318272665
Left
0.95338868265243
Left
0.9822489551465043
Left
0.7462156028150145
Left
0.9728761475398888
Left
0.9611433318272665
Left
0.8752703633993194
Left
0.9822489551465043
Left
0.9420684108893576
Left
0.95338868265243
Left
0.7096360056069901
Left
0.6855629559539462
Left
0.7462156028150145
Left
0.9966482796096178
Left
0.9420684108893576
Left
0.9822489551465043
Left
0.9148257284353466
Left
0.9254239127575978
Left
0.84331649453353
Left
0.9931531162628318
Left
0.9894081760478759
Left
0.44982791103942854
Right
0.9148257284353466
Left
0.9254239127575978
Left
0.9894081760478759
Left
0.46262772324766915
Right
0.44982791103942854
Right
0.9917164439949772

Left
0.9937696130487768
Left
0.7890964292773458
Left
0.9338817375901171
Left
0.9359899071544867
Left
0.9917164439949772
Left
0.9209507441746894
Left
0.9937696130487768
Left
0.8195357680267555
Left
0.8787682426295289
Left
0.9338817375901171
Left
0.35881962996488825
Right
0.8787682426295289
Left
0.39819564396189217
Right
0.9684504456091689
Left
0.37121384584459777
Right
0.9936183822776451
Left
0.974347671060517З
Left
0.9899141547920952
Left
0.6174728227984922
Right
0.8021810684713792
Left
0.9899141547920952
Left
0.9684504456091689
Left
0.9402702376634287
Left
0.9936183822776451
Left
0.5516811229058828
Left
0.9196391841976358
Left
0.37121384584459777
Right
0.7540110657838195
Left
0.9402702376634287
Left
0.9743476710605173
Left
0.9062226514282471
Left
0.3820067013624183
Right
0.9772896476217972
Left
0.9359789272722828
Left
0.9885503134330745
Left
0.9859512746016549
Left
0.918172484567357
Left
0.926695814388605
Left

```
0.9772896476217972
Left
0.9885503134330745
Left
0.4904534100495921
Right
0.9859512746016549
Left
0.4904534100495921
Right
0.9840803960697755
Left
0.9830953251625819
Left
0.8246320108724589
Left
0.9339851192219057
Left
0.9742210946142087
Left
0.9340226402633245
Left
0.9830953251625819
Left
0.9840803960697755
Left
0.9877542937101121
Left
0.8369809868732206
Left
0.9529389556665637
Left
0.9339851192219057
Left
0.9165376832636434
Left
0.5888748501334558
Left
0.9742210946142087
Left
0.8246320108724589
Left
0.9340226402633245
Left
0.8369809868732206
Left
0.5888748501334558
Left
0.9610896091745622
Left
0.8440574965883695
Left
0.9789949454217545
Left
0.8187578291283613
Left
0.9950459775743616
Left
0.7701341569045096
Left
0.053833868875404915
Right
0.9610896091745622
Left
0.9789949454217545
Left
0.9950459775743616
Left
0.7701341569045096
Left
0.8440574965883695
Left
0.9789949454217545
Left
0.1536679458611908
Right
0.9986985071050143
```

Left
0.9087452087801907
Left
0.9986985071050143
Left
0.9087452087801907
Left
0.9892408164327222
Left
0.9087452087801907
Left
0.18927868289788397
Right
0.9892408164327222
Left
0.7060289973370131
Left
0.8516094144446876
Left
0.905086157170679
Left
0.8516094144446876
Left
0.9432652689556511
Left
0.6177850658464895
Left
0.4646506935547059
Left
0.990994520082568
Left
0.8820320456271037
Left
0.8916856427246771
Left
0.990994520082568
Left
0.8916856427246771
Left
0.990994520082568
Left
0.9603541164657194
Left
0.9426983425095306
Left
0.9426983425095306
Left
0.9603541164657194
Left
0.963316826150573
Left
0.9426983425095306
Left
0.5747207232364414
Right
0.4093535342776969
Right
0.989238652072837
Left
0.5747207232364414
Right
0.989238652072837
Left
0.5757840366788696
Left
0.4234077367859415
Right
0.9615758479910338
Left
0.5757840366788696
Left
0.9615758479910338
Left
0.8313556036673061
Left
0.4320092771823249
Right

```
0.5750196473917903
Left
0.9851058336025954
Left
0.4320092771823249
Right
0.9770739568593986
Left
0.5750196473917903
Left
0.9677301593531965
Left
0.5750196473917903
Left
0.9770739568593986
Left
```

In [282…

```
len(AP_predictions_proba_AP)
```

Out[282…

```
188
```

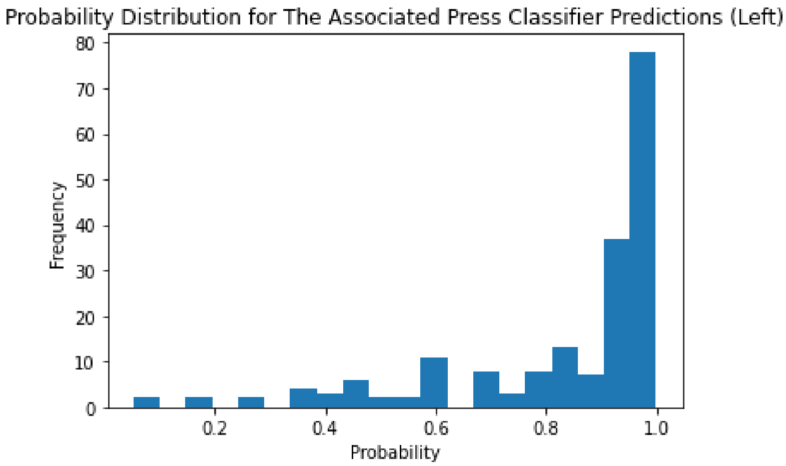
In [283…

```
#from sklearn.svm import SVC
#svm = SVC(kernel='linear', probability=True)
#svm.fit(X_train_tf, Y_train)

#AP_predictions_proba = svm.predict_proba(X_Data_Centered)

for paAP in range(0,len(AP_predictions_proba_AP)):
    for pa2AP in range(0,1):
        if (AP_predictions_proba_AP[paAP][pa2AP] <= 0.65) & \
        (AP_predictions_proba_AP[paAP][pa2AP] >= 0.5):
            print(pa, ':', AP_predictions_proba_AP[paAP][pa2AP],
                  Data_Classification_Centered_AP[paAP])
```

```
180 : 0.5336534447481074 Right
180 : 0.6174728227984922 Right
180 : 0.5516811229058828 Left
180 : 0.5888748501334558 Left
180 : 0.5888748501334558 Left
180 : 0.6177850658464895 Left
180 : 0.5747207232364414 Right
180 : 0.5747207232364414 Right
180 : 0.5757840366788696 Left
180 : 0.5757840366788696 Left
180 : 0.5750196473917903 Left
180 : 0.5750196473917903 Left
180 : 0.5750196473917903 Left
```

In [286…

```
#AP_predictions_proba

plt.hist(AP_predictions_proba_AP[:, 0], bins=20)
plt.xlabel('Probability')
plt.ylabel('Frequency')
plt.title('Probability Distribution for The Associated Press Classifier Predictions (Left)')
plt.show()
```



As could be expected from the AllSides experts, the Associated Press online publication is, in fact more confidently left leaning. Since all our left leaning data was first order left lean, this makes sense. The distribution for left leaning data is pretty confident when it is leaning and most articles are categorized as left leaning."

FOX vs MSNBC political audience disparities (presentation data)

In [ ]:

```
MSNBC_political_demographic = [['MSN',0.95, 0.05],['FOX',0.07, 0.93]]
FOX_political_demographic = []
News_political_demographic=pd.DataFrame(MSNBC_political_demographic)
```

In [ ]:

```
News_political_demographic.head()
```

	0	1	2
0	MSN	0.95	0.05
1	FOX	0.07	0.93

In [ ]:

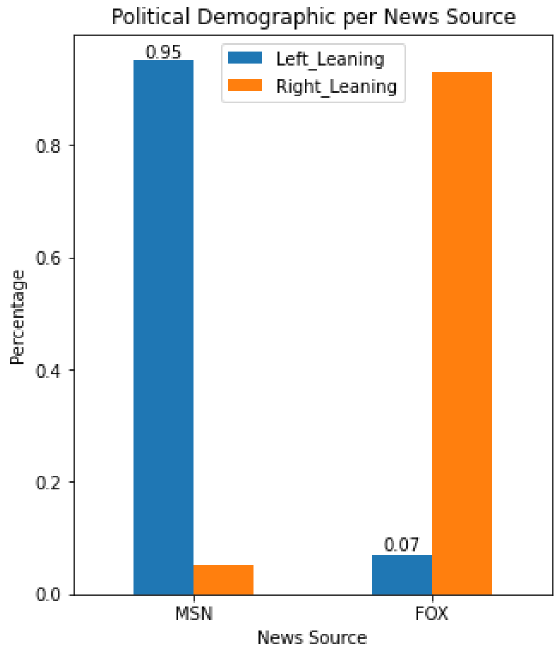
```
News_political_demographic.rename (columns = {0:'News_Source'}, inplace=True)
News_political_demographic.rename (columns = {1:'Left_Leaning'}, inplace=True)
News_political_demographic.rename (columns = {2:'Right_Leaning'}, inplace=True)
```

In [474…

```
ax2=News_political_demographic.plot(kind="bar", x='News_Source',rot=0,
                                    legend=True,
                                    figsize=(5,6),
                                    xlabel='News Source',
                                    ylabel='Percentage',
                                    title='Political Demographic per News Source')
ax2.bar_label(ax2.containers[0])
```

Out[474…

```
[Text(0, 0, '0.95'), Text(0, 0, '0.07')]
```



Concentration ratio Charts (presentation data)

In [475…

```
Concentration_Ratios=[['Right','nyc',17.49],['Right','reparations',16.89],['Right','aliens',12.7],
                      ['Right','ccp',11.5],['Right','locker',11.07],['Right','comey',9.58],
                      ['Right','lula',9.2],['Right','busch',8.9],['Right','fidelity',8.77],
                      ['Left','anonymity',17.39],['Left','thomnass',16.14],['Left','willis',14.19],
                      ['Left','mehta',13.6],['Left','docket',13.08],['Left','ginni',12.24],
                      ['Left','pork',11.59],
                      ['Left','uncertainty',9.54],['Left','hush',9.74],['Left','gorsuch',9.74]]

Concentration_Ratios_df=pd.DataFrame(Concentration_Ratios)
```

In [476…

```
Concentration_Ratios_df.rename (columns = {0:'Political_Lean'}, inplace=True)
Concentration_Ratios_df.rename (columns = {1:'Word'}, inplace=True)
Concentration_Ratios_df.rename (columns = {2:'Factor_of_Concentration'}, inplace=True)
```

In [477…

```
Concentration_Ratios_df.head()
```

Out[477…

	Political_Lean	Word	Factor_of_Concentration
0	Right	nyc	17.49
1	Right	reparations	16.89
2	Right	aliens	12.70
3	Right	ccp	11.50
4	Right	locker	11.07

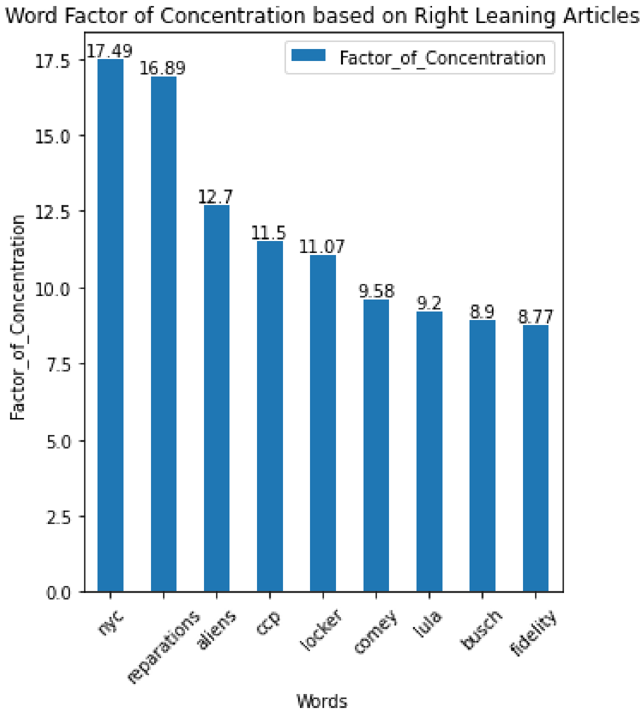
In [478…

```
ax3=Concentration_Ratios_df[Concentration_Ratios_df['Political_Lean']=='Right'].plot(kind="bar",
                                                                                      x='Word',rot=45,
                                  legend=True,
                                  figsize=(5,6),
                                  xlabel='Words',
                                  ylabel='Factor_of_Concentration',
                                  #='Political_Lean',
                                  title='Word Factor of Concentration based on Right Leaning Articles')
ax3.bar_label(ax3.containers[0])
```

Out[478…

```
[Text(0, 0, '17.49'),
 Text(0, 0, '16.89'),
 Text(0, 0, '12.7'),
 Text(0, 0, '11.5'),
 Text(0, 0, '11.07'),
 Text(0, 0, '9.58'),
```

```
 Text(0, 0, '9.2'),
 Text(0, 0, '8.9'),
 Text(0, 0, '8.77')]
```

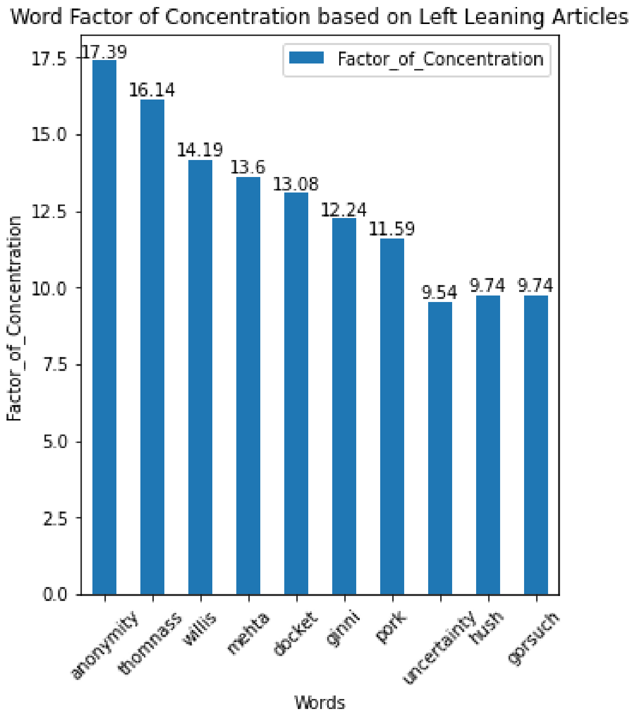


In [479…

```
ax3=Concentration_Ratios_df[Concentration_Ratios_df['Political_Lean']=='Left'].plot(kind="bar",
                                                                                     x='Word',rot=45,
                                  legend=True,
                                  figsize=(5,6),
                                  xlabel='Words',
                                  ylabel='Factor_of_Concentration',
                                  #='Political_Lean',
                                  title='Word Factor of Concentration based on Left Leaning Articles')
ax3.bar_label(ax3.containers[0])
```

Out[479…

```
[Text(0, 0, '17.39'),
 Text(0, 0, '16.14'),
 Text(0, 0, '14.19'),
 Text(0, 0, '13.6'),
 Text(0, 0, '13.08'),
 Text(0, 0, '12.24'),
 Text(0, 0, '11.59'),
 Text(0, 0, '9.54'),
 Text(0, 0, '9.74'),
 Text(0, 0, '9.74')]
```


Word Factor of Concentration based on Left Leaning Articles
Factor_of_Concentration
Factor_of_Concentration
17.39
16.14
14.19
13.6
13.08
12.24
11.59
9.54
9.74
9.74
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
anonymity
thomnass
willis
mehta
docket
ginni
pork
uncertainty
hush
gorsuch
Words

In [ ]: