Rachit Khandelwal
Prashant Raiger

April 23, 2020

Final Report

1 Setting up

1.1 Change work directory

[1]:
```
import os
os.chdir("/Users/WaferHsu/Desktop/AU/2020Spring/STAT-696-NLP/
↪FinalProj_Alex_Wafer")
```

1.2 Import packages

[2]:
```
# nltk
import nltk
from nltk.stem import WordNetLemmatizer
lemmatizer = WordNetLemmatizer()
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
stopWords = set(stopwords.words('english'))

# numpy
import numpy as np

# regex
import re

# pandas df
import pandas as pd

# plot
import matplotlib.pyplot as plt
import seaborn as sns

# used to remove Pandas warnings
```

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

# sentiment analysis (vader)
from nltk.sentiment.vader import SentimentIntensityAnalyzer

# normalize data
from sklearn.preprocessing import MinMaxScaler

# train/test split
from sklearn.model_selection import train_test_split

# Regression
import statsmodels.formula.api as sm
from sklearn import linear_model

# tfidf
from sklearn.feature_extraction.text import TfidfVectorizer

# NMF (topic modeling)
from sklearn.decomposition import NMF

# KMeans Clustering
from sklearn.cluster import KMeans

# classifying modules
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import RidgeClassifier

# sklearn (classification)
from sklearn.metrics import classification_report
from sklearn.metrics import f1_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score

# Visualizing Clusters
import matplotlib as mpl
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.manifold import MDS
```

1.3 Load original dataset

[3]:
```
data = pd.read_csv("./data/kaggle_RC_2019-05.csv", encoding = "utf8")
```

- Take a brief look at the data.

[4]:
```
data.head(3)
```

[4]:
```
        subreddit                                               body  \
0  gameofthrones  Your submission has been automatically removed…
1            aww  Dont squeeze her with you massive hand, you me…
2         gaming  It's pretty well known and it was a paid produ…

   controversiality  score
0                 0      1
1                 0     19
2                 0      3
```

- Check missing values: Fortunately, we do not need to deal with NA values data.

[5]:
```python
data.isna().describe()
```

[5]:
```
        subreddit     body  controversiality    score
count     1000000  1000000           1000000  1000000
unique          1        1                 1        1
top         False    False             False    False
freq      1000000  1000000           1000000  1000000
```

- Check the “body” variable is a string variable.

[6]:
```python
data.dtypes
```

[6]:
```
subreddit           object
body                object
controversiality     int64
score                int64
dtype: object
```

[7]:
```python
type(data["body"][0])
```

[7]:
```
str
```

2 Exploratory Data Analysis (EDA)

- Descriptive statistics for continuous variables. The maximum and minimum has a hugh difference.

[43]:
```python
data.describe()
```

[43]:
```
        controversiality           score
count     1000000.000000  1000000.000000
mean            0.029583       11.510103
std             0.169434      149.671560
min             0.000000     -889.000000
25%             0.000000        1.000000
50%             0.000000        2.000000
```

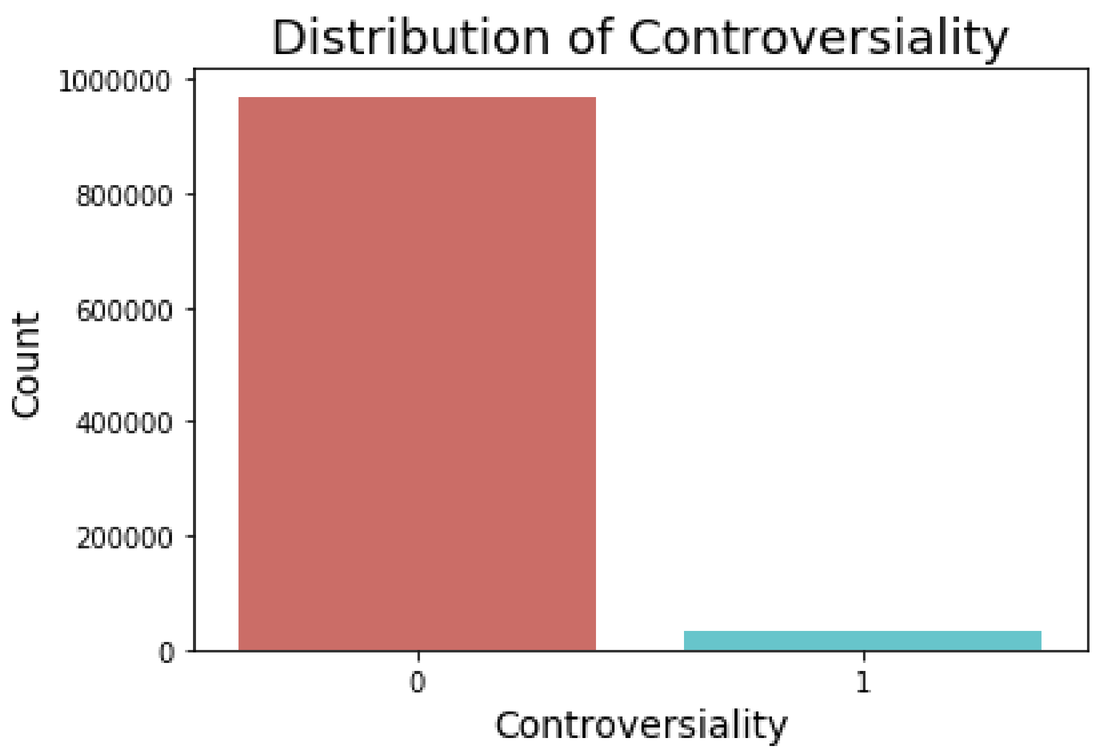
```
75%            0.000000       4.000000
max            1.000000   35619.000000
```

2.1 Controversiality

- The distribution of controversiality. It is heavily discrete distributed. There are so many less data in controversiality = 1.

[24]:
```
plt.figure(figsize = (6, 4))
sns.countplot(data.controversiality, palette = "hls")
plt.title("Distribution of Controversiality", fontsize = 18)
plt.ylabel("Count", fontsize = 14)
plt.xlabel("Controversiality", fontsize = 14)
```

[24]:
```
Text(0.5, 0, 'Controversiality')
```



- The frequency of controversiality.

[12]:
```
print(data.controversiality.value_counts())
```

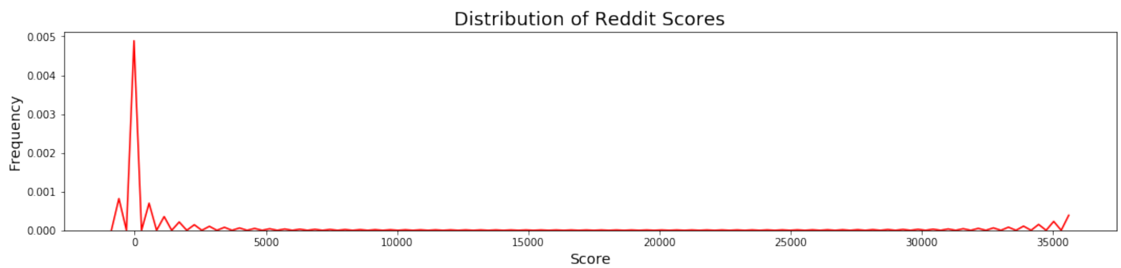
```
0    970417
1     29583
Name: controversiality, dtype: int64
```

2.2 Score

Reddits scores (up reddits minus down reddits) are heavily skewed right. Data mainly distributed lower than 3000, and there are a lot of outliers.

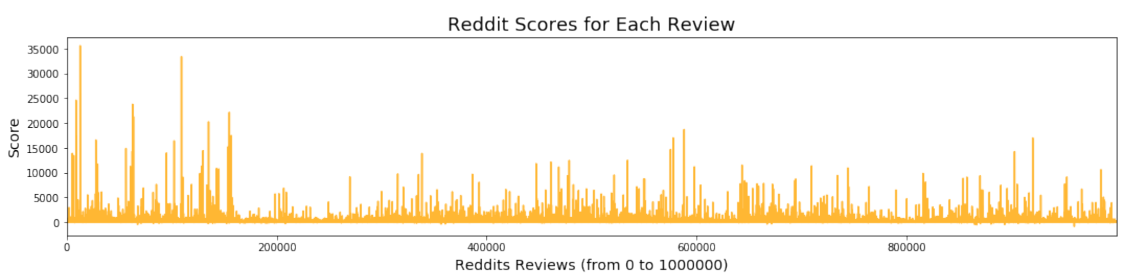
[36]:
```
plt.figure(figsize = (18, 3.5))
sns.distplot(data.score, hist = False, color = "red", bins = 10)
plt.title("Distribution of Reddit Scores", fontsize = 18)
plt.ylabel("Frequency", fontsize = 14)
plt.xlabel("Score", fontsize = 14)
```

[36]: Text(0.5, 0, 'Score')



[41]:
```
plt.figure(figsize = (18, 3.5))
data.score.plot(color = 'orange', alpha = 0.8)
plt.title("Reddit Scores for Each Review", fontsize = 18)
plt.ylabel("Score", fontsize = 14)
plt.xlabel("Reddits Reviews (from 0 to 1000000)", fontsize = 14)
```

[41]: Text(0.5, 0, 'Reddits Reviews (from 0 to 1000000)')



2.3 Subreddit

Frequency Counts of the column "subreddit". Each category has 25000 reviews. Based on the subreddits, we could sort them out to some broader topics like "sports", "news & politics", "movies", "slangs", "online games/video games", and see the classification between two (or more) similar groups. After filtering similar topics out, we are looking at the body text for sentiment analysis, topic modeling, and clustering to see if there is anything interesting results within the data. This project will focus on the category of politics.

[44]:
```python
data["subreddit"].value_counts()
```

[44]:
```
The_Donald             25000
gonewild               25000
Market76               25000
worldnews              25000
ChapoTrapHouse         25000
apexlegends            25000
marvelstudios          25000
Animemes               25000
RoastMe                25000
soccer                 25000
unpopularopinion       25000
nfl                    25000
todayilearned          25000
Pikabu                 25000
gaming                 25000
funny                  25000
videos                 25000
leagueoflegends        25000
dankmemes              25000
teenagers              25000
gameofthrones          25000
wallstreetbets         25000
asoiaf                 25000
hockey                 25000
MortalKombat           25000
memes                  25000
freefolk               25000
relationship_advice    25000
trashy                 25000
politics               25000
movies                 25000
FortNiteBR             25000
pics                   25000
AskReddit              25000
aww                    25000
nba                    25000
Showerthoughts         25000
news                   25000
SquaredCircle          25000
AmItheAsshole          25000
Name: subreddit, dtype: int64
```

3 Subset politics data by subreddit and the exploration

[46]:
```
politics_data = data[data["subreddit"] == "politics"]
```

[47]:
```
politics_data = politics_data.reset_index(drop = True) # reset index
```

[48]:
```
politics_data.head()
```

[48]:
```
  subreddit                                               body  \
0  politics  Yes, there is a difference between gentle supp…
1  politics  He also got married, and they filed jointly fo…
2  politics  So you think we can just tell people they no l…
3  politics      ITT, lots of people without jobs complaining.
4  politics                       "You boys wanna shovel some coal?"

   controversiality  score
0                 0      1
1                 0     12
2                 0      1
3                 0     -6
4                 0     17
```

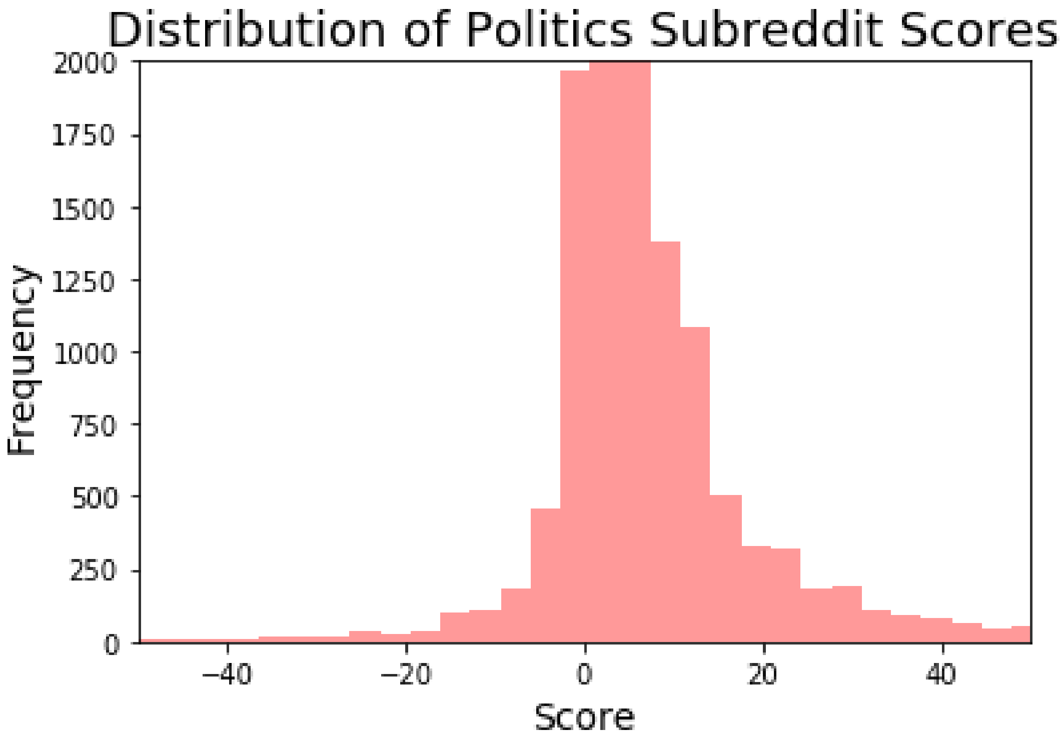
3.1 Distribution of Subreddit

Re-formatted histogram of politics subreddit scores with x-axis limits from (-50, 50) and y-axis limits from (0, 2000).

[50]:
```
%%time
sns.distplot(politics_data["score"], kde = False, color = "red", bins = 3000)
plt.title("Distribution of Politics Subreddit Scores", fontsize = 18)
plt.ylabel("Frequency", fontsize = 14)
plt.xlabel("Score", fontsize = 14)
plt.xlim(-50,50)
plt.ylim(0, 2000)
# most scores fall within 0 to 20 and there are a lot more observations between␣
↪0 and 20 than 2000
```

```
CPU times: user 2.67 s, sys: 111 ms, total: 2.78 s
Wall time: 2.79 s
```

[50]: (0, 2000)



3.2 Creation of New body_length Variable

Counting number of characters in (uncleaned) body variable.

[63]:
```
politics_data["body_length"] = [len(el) for el in politics_data["body"]]
```

[64]:
```
politics_data.head()
```

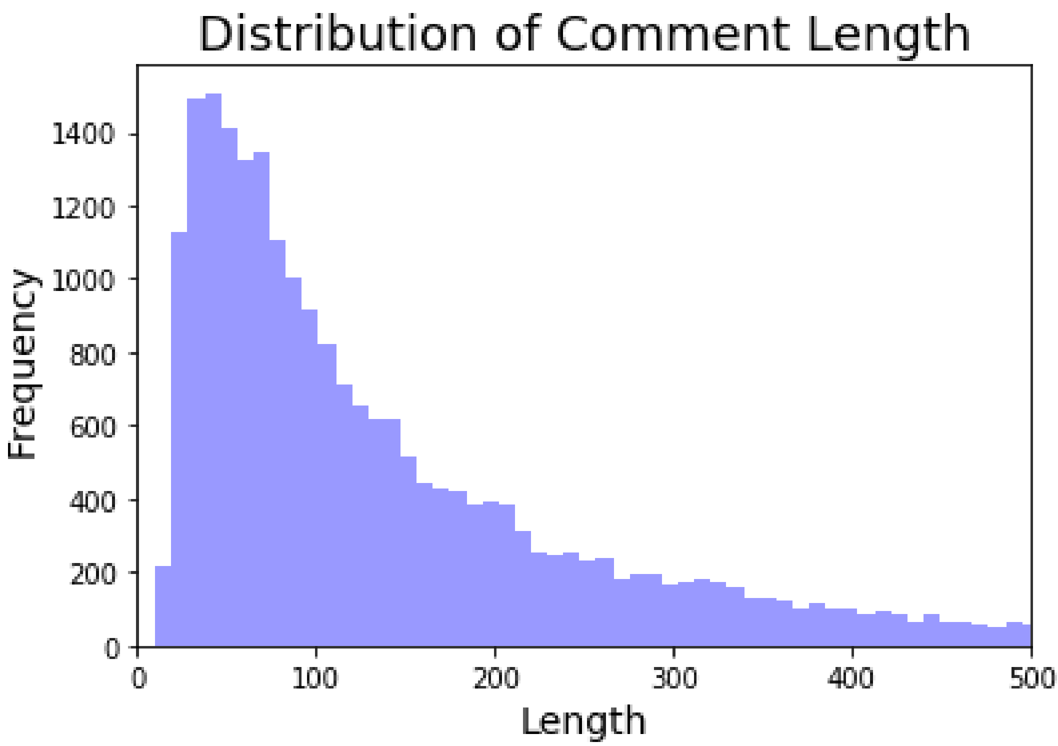
[64]:
```
  subreddit                                               body  \
0  politics  Yes, there is a difference between gentle supp…
1  politics  He also got married, and they filed jointly fo…
2  politics  So you think we can just tell people they no l…
3  politics      ITT, lots of people without jobs complaining.
4  politics                 "You boys wanna shovel some coal?"

   controversiality  score  body_length
0                 0      1          101
1                 0     12          145
2                 0      1           89
3                 0     -6           45
4                 0     17           34
```

3.3 Distribution of body_length (Histogram)

Data visualizing the body_length variable to see the data pattern. The body length is skewed to the right.

[62]:
```
sns.distplot(politics_data.body_length, kde = False, color = "blue", bins =␣
 ↪1000)
plt.title("Distribution of Comment Length", fontsize = 18)
plt.ylabel("Frequency", fontsize = 14)
plt.xlabel("Length", fontsize = 14)
plt.xlim(0, 500)
```

[62]: (0, 500)



3.4 Summary statistics on continuous variables

The maximum in `score` is 9715 but the mean is 13, data is strongly discreated. Same situation in `body_length`, which maximun is 9156 but its mean is 212.

[60]:
```
politics_data.describe()
```

[60]:

	controversiality	score	body_length
count	25000.00000	25000.000000	25000.000000
mean	0.03224	13.809040	212.050040

```
std            0.17664    141.260591    298.831188
min            0.00000   -383.000000     10.000000
25%            0.00000      1.000000     59.000000
50%            0.00000      2.000000    113.000000
75%            0.00000      6.000000    242.000000
max            1.00000   9715.000000   9156.000000
```

4 Pre-processing politics_data

4.1 Spelling error checking

Test abbreviations or spelling errors. To be honest, there are a lot of things to do to fix the spelling error, my code below is incompleted, but this methodology helps me to understand how much more things I need to consider in the future data analysis.

Reference: https://medium.com/@indreshbhattacharyya/remaking-of-shortened-sms-tweet-post-slangs-and-word-contraction-into-sentences-nlp-7bd1bbc6fcff

- Test abbreviations: "wd", "bt", "der", "hs", "dt", "nt". According to the output, 'hs' = spelling error; 'dt' = (probably) doubt; 'nt' = not.

[65]:
```python
abbre_list = ["wd", "bt", "der", "hs", "dt", "nt"]


# make a list by "macthlist", find macches from the "politics_data"
matchlist_test = [" " + abbre_list[i] + " " for i in range(len(abbre_list))]
print("Add space before and after in order to test the word in reddits",␣
↪matchlist_test)
print()

# print all matches by the "politics_data"
print("Matching reddits: ")
print()
for abbr in matchlist_test:
    for rv in politics_data["body"]:
        if abbr in rv:
            print("-----"+abbr+"-----")
            print(rv)
            print()
```

```
Add space before and after in order to test the word in reddits [' wd ', ' bt ',
' der ', ' hs ', ' dt ', ' nt ']

Matching reddits:

----- hs -----
I think my favourite moment is the one where cartman pretends his hand is a
conman pretending to be Jennifer lopez. The moment Kyle decides to believe him
```

```
and he goes Ha ha hs ha ha ha, I got you kinda

----- dt -----
I'm not going to hold my breath. I just listened to Grassley on C-span and
they're entrenched into the myth that barr/mueller exonerated dt - and they're
continuing to spread that myth/propaganda widely.  Today's hearing with barr
will be fascinating!
https://www.youtube.com/watch?v=CK2GNiXdE3c

----- nt -----
Didnt not nt mean it.
```

4.2 Text Clean, Tokenize, and Lemmatization

- Write functions to clean and lemmatize "body" variable.

[67]:
```
### text cleaning
def textCleaner(text):
    output = text

    #lowercase
    output = output.lower()

    # fix contractions
    output = output.replace("’", "'")
    output = output.replace("can't", "can not")
    output = output.replace("won't", "will not")
    output = output.replace("n't", " not")
    output = output.replace("\'ll", " will")
    output = output.replace("\'ve", " have")
    output = output.replace("\'d", " would")
    output = output.replace("\'s", " is")
    output = output.replace("\'m", " am")
    output = output.replace("\'re", " are")

    # remove stop words
    clean_sentence = []
    for word in output.split():
        if word not in stopWords:
            clean_sentence.append(word)
    output = " ".join(clean_sentence)

    # remove email addresses & Internet domains
    output = re.sub(r'r\/\S+', '', output)
    output = re.sub(r'http\S+', '', output)
    output = re.sub("\S*@\S*\s?", "", output)
    output = re.sub("\S*\.edu|\.com|\.gov|\.net\S*\s?", "", output)
```

```
    output = re.sub("@\S*", "", output)

    # remove punctuations
    output = re.sub("[^a-zA-Z\s]", "", output)

    return(output)


### tokenize & lemmatiztion
def textNormalization(corpus):
    output = corpus

    # in the text, lemmatize each word in the tokenized list
    output = [lemmatizer.lemmatize(w) for w in word_tokenize(output)]

    # rejoin all the words into one string by a space
    output = " ".join(output)

    return(output)
```

- Apply functions to the body variable.

[82]:
```
politics_data["body"] = politics_data["body"].apply(textCleaner)
politics_data["body"] = politics_data["body"].apply(textNormalization)

# briefly print the variable
politics_data["body"].head()
```

[82]:
```
0    yes difference gentle suppression hard suppres…
1    also got married filed jointly husband income …
2               think tell people longer right express
3               itt lot people without job complaining
4                                boy wan na shovel coal
Name: body, dtype: object
```

4.3 Distribution of *cleaned* body_length (Histogram)

- Change body_length from characters to number of words.

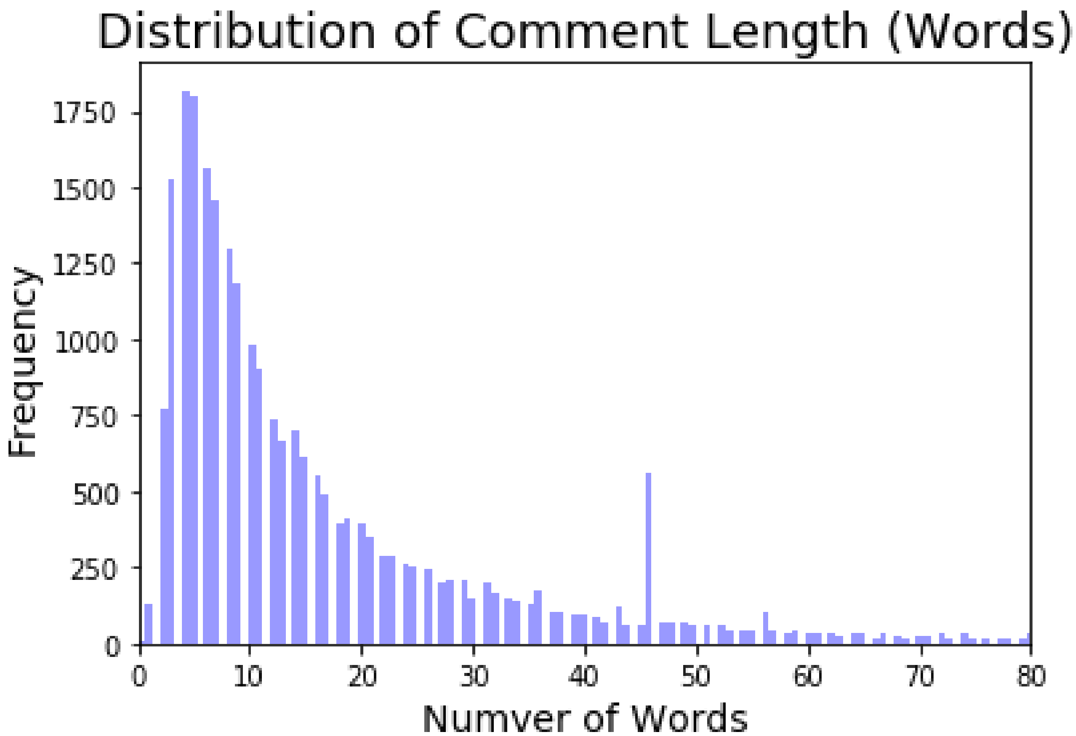
[74]:
```
politics_data["body_length"] = [len(el.split()) for el in politics_data["body"]]
```

- The distribution of the body_length variable.

[79]:
```
sns.distplot(politics_data["body_length"], kde = False, color = "blue", bins =␣
 ↪1000)
plt.title("Distribution of Comment Length (Words)", fontsize = 18)
plt.ylabel("Frequency", fontsize = 14)
plt.xlabel("Numver of Words", fontsize = 14)
```

```
plt.xlim(0, 80)
```

[79]: (0, 80)



4.4 Make a Text Corpus

- For body variable, make a corpus for topic modelling.

[83]:
```
corpus = list(politics_data["body"])

# briefly print the corpus
corpus[0:7]
```

[83]:
```
['yes difference gentle suppression hard suppression neither good thing',
 'also got married filed jointly husband income teacher number number',
 'think tell people longer right express',
 'itt lot people without job complaining',
 'boy wan na shovel coal',
 'everything power make sure biden get nomination fall line doe primary
coronation',
 'according mueller bar lied misrepresented pretty much everything democrat need
impeach ag']
```

5 Sentiment Analysis

5.1 Harvard IV-4 scoring

- Read in dataset, separate to positive and negative values, and drop NA values.

[86]:
```
# read Harvard IV-4 sentiment data
harvard = pd.read_excel("./data/dict_Harvard.xls")

# extract positive & negative lists
harvard_pos = harvard[["Entry", "Positiv"]].dropna()
harvard_neg = harvard[["Entry", "Negativ"]].dropna()
```

- Check the lengths of the datasets.

[87]:
```
print("Length of positive dictionary: ", len(harvard_pos))   # 1915 rows
print("Length of negative dictionary: ", len(harvard_neg))   # 2291 rows
```

```
Length of positive dictionary:  1915
Length of negative dictionary:  2291
```

- Take a look at the dictionary, all words are capitalized.

[92]:
```
print(harvard_pos.head())
print(harvard_neg.head())
```

```
      Entry  Positiv
8     ABIDE  Positiv
9   ABILITY  Positiv
11     ABLE  Positiv
18   ABOUND  Positiv
41  ABSOLVE  Positiv
         Entry  Negativ
2      ABANDON  Negativ
3  ABANDONMENT  Negativ
4        ABATE  Negativ
6     ABDICATE  Negativ
7        ABHOR  Negativ
```

- Make a function to clean dictionaries (lowercase, remove punctuation).

[93]:
```
def harvardCleaner(word):
    output = word

    # lowercase
    output = str(word).lower()
    # remove punctuations
    output = re.sub("[^a-zA-Z]", "", output)

    return(output)
```

- Make a Harvard IV-4 scorer function for applying it to the `politics_data`.

[94]:
```python
def harvardScorer(text_input, sentiment_list):

    # GET NUMERATOR
    numerator = 0
    for word in str(text_input).split():
        if word in list(sentiment_list):
            numerator += 1
        else:
            numerator += 0
    # GET DENOMINATOR
    denominator = len(str(text_input).split())

    # CALCULATE SENTIMENT SCORE
    if denominator == 0:
        sentiment_score = 0
    else:
        sentiment_score = numerator/denominator

    return(float(sentiment_score))
```

- Apply the function for cleaning dictionaries and drop duplicated words.

[95]:
```python
# apply function: harvardCleaner
harvard_pos["Entry"] = harvard_pos["Entry"].apply(harvardCleaner)
harvard_neg["Entry"] = harvard_neg["Entry"].apply(harvardCleaner)

# drop duplicated words
harvard_pos.drop_duplicates("Entry", "first", inplace = True)
harvard_neg.drop_duplicates("Entry", "first", inplace = True)
```

- View the length of the dictionaries.

[96]:
```python
print("Length of positive dictionary: ", len(harvard_pos))   # 1636 rows
print("Length of negative dictionary: ", len(harvard_neg))   # 2005 rows
```

```
Length of positive dictionary:  1636
Length of negative dictionary:  2005
```

- Create new variables in the data frame to store `Positive_Score` and `Negatice_Score`.

[97]:
```python
# Positive Score
politics_data["Positive_Score"] = politics_data.apply(lambda x:
                                                       harvardScorer(x['body'],␣
 ↪harvard_pos["Entry"]),
                                                       axis = 1)
# negative score
politics_data["Negative_Score"] = politics_data.apply(lambda x:
```

```
                                                        harvardScorer(x['body'],␣
↪harvard_neg["Entry"]),
                                                        axis = 1)
```

- Create new variable "net_score" that is the difference of the positive and negative scores.

[98]:
```
politics_data["net_score"] = politics_data["Positive_Score"] -␣
↪politics_data["Negative_Score"]
```

- Preview the `politics_data`

[99]:
```
politics_data.head(5)
```

[99]:
```
  subreddit                                               body  \
0  politics  yes difference gentle suppression hard suppres…
1  politics  also got married filed jointly husband income …
2  politics               think tell people longer right express
3  politics               itt lot people without job complaining
4  politics                               boy wan na shovel coal

   controversiality  score  body_length  Positive_Score  Negative_Score  \
0                 0      1            9        0.222222        0.333333
1                 0     12           10        0.100000        0.000000
2                 0      1            7        0.166667        0.000000
3                 0     -6            6        0.000000        0.000000
4                 0     17            6        0.000000        0.000000

   net_score
0  -0.111111
1   0.100000
2   0.166667
3   0.000000
4   0.000000
```

5.2 Slang dictionary scoring

- Import the slang dictionary as a pandas df and change column names.

[100]:
```
slangSD = pd.read_csv("./data/dict_slangSD.txt", sep = "\t")
slangSD.columns = ["word", "score"]
```

- There are 96460 rows from slang dictionary, and the word entries have not cleaned yet.

[102]:
```
print("Length of dataframe ", len(slangSD))
slangSD.head()
```

```
Length of dataframe  96460
```

[102]:

```
      word  score
0      a'f      1
1   a'ight     -1
2  a'nnesia    -1
3   a'pcha      0
4      a's      1
```

- Create a cleaning function for cleaning the slangSD data frame. The dataframe as multi-gram words, punctuations, conjunctions, and different cases that need to be cleaned. This reduces the scoring ability, but is necessary to generate the scores.

[103]:

```python
def slangCleaner(text):
    output = text

    # fix contractions -1
    contraction_map = {"ain't": "is not", "can't": "cannot",
                       "dont": "do not", "how'd": "how did",
                       "i'd've": "i would have", "let's": "let us",
                       "ma'am": "madam", "o'clock": "of the clock",
                       "shan't": "shall not", "sha'n't": "shall not",
                       "should've": "should have", "so's": "so as",
                       "where'd": "where did", "won't": "will not",
                       "wouldn't": "would not", "y'all": "you all",
                       "you'd": "you would"}
    for i in range(len(contraction_map)):
        output = output.replace(list(contraction_map.items())[i][0],
                                list(contraction_map.items())[i][1])

    # fix contraction - 2
    output = output.replace("n't", " not")
    output = output.replace("\'ll", " will")
    output = output.replace("\'ve", " have")
    output = output.replace("\'d", " would")
    output = output.replace("\'s", " is")
    output = output.replace("\'m", " am")
    output = output.replace("\'re", " are")

    # remove email addresses & Internet domains
    output = re.sub(".?@.?", "", output)
    output = re.sub("\S*\.com|\.net\S*\s?", "", output)

    # remove punctuations
    output = re.sub("[^a-zA-Z\s]", "", output)

    return(output)
```

- Apply clean function, drop duplicates, and preview the slangSD dataset.

[106]:
```
# apply function
slangSD["word"] = slangSD["word"].apply(slangCleaner)

# drop duplicates, "first", keeps the first entry
slangSD.drop_duplicates("word", "first", inplace = True)

# reset index
slangSD = slangSD.reset_index(drop = True)

# preview cleaned slangSD
slangSD.head()
```

[106]:

	word	score
0	af	1
1	aight	-1
2	annesia	-1
3	apcha	0
4	a is	1

- Briefly test slangSD to make sure the cleaning function does work. The output looks qualified.

[109]:
```
# test slangSD
def text_wd(word):
    for el in slangSD["word"]:
        if word in el:
            print(el)
text_wd("should have")

# 2nd way for testing
slangSD[slangSD["word"] == "have"]
```

[109]:

	word	score	gram
42646	have	0	1

- Test if there is any duplicated word.

[110]:
```
slangSD[slangSD["word"] == "a"]
```

[110]:

	word	score	gram
7	a	0	1

- Check the length of the cleaned dataset, there are 94292 rows.

[107]:
```
len(slangSD["word"])
```

[107]: 94292

- Make a new variable that is the count of the words in the slang term –> More than 1-gram words are removed because it will take too much computing power to count sentiments of all

1, 2, 3, etc. gram words and the frequency of multi-gram slang decreases with gram length.

[ ]:
```
# keep 1-gram only
slangSD["gram"] = 0

for i in range(len(slangSD)):
    slangSD["gram"][i] = len(slangSD["word"][i].split())

slangSD = slangSD[slangSD["gram"] < 2]
```

- Check the length of the new subsetted data frame – it is reduced by ~ 30,000.

[43]:
```
len(slangSD)    # 59,227
```

[43]:
```
59228
```

- Create a slang sentiment score function with nuanced numerator calculation changes.

[115]:
```
def slangScorer(text_input, sentiment_list):

    # GET NUMERATOR
    numerator = 0
    for word in str(text_input).split():
        if word in list(sentiment_list):
            numerator += int(slangSD["score"][slangSD["word"] == word])
        else:
            numerator += 0
    # GET DENOMINATOR
    denominator = len(str(text_input).split())

    # CALCULATE SENTIMENT SCORE
    if denominator == 0:
        sentiment_score = 0
    else:
        sentiment_score = numerator/denominator

    return(sentiment_score)
```

- Run slang scorer on data frame and store in new variable — **takes a LONG time**! You may import the .csv for saving time.

[46]:
```
%%time
politics_data["slang_score"] = politics_data.apply(lambda x:␣
 ↪slangScorer(x['body'],                                                    ␣
 ↪slangSD["word"]),
                                                    axis = 1)
politics_data
```

```
CPU times: user 36min 40s, sys: 6.33 s, total: 36min 46s
Wall time: 36min 59s
```

[46]:

```
      subreddit                                               body  \
0      politics  yes difference gentle suppression hard suppres…
1      politics  also got married filed jointly husband income …
2      politics  think tell people longer right express themselves
3      politics             itt lot people without job complaining
4      politics                         you boy wan na shovel coal
…         …                                                   …
24995  politics  everyone care truth justice incensed no includ…
24996  politics  big question senate never openly refused enter…
24997  politics  report literally say president cooperative eno…
24998  politics  ok let play unfun little game barr gave series…
24999  politics                                yay solves problem

       controversiality  score  body_length  Positive_Score  Negative_Score  \
0                     0      1            9        0.222222        0.333333
1                     0     12           10        0.100000        0.000000
2                     0      1            7        0.142857        0.000000
3                     0     -6            6        0.000000        0.000000
4                     0     17            6        0.000000        0.000000
…                   …    …          …             …              …
24995                 0      3            8        0.375000        0.000000
24996                 0      2          152        0.105263        0.046053
24997                 0      2           14        0.214286        0.071429
24998                 0      7           21        0.190476        0.142857
24999                 0      0            3        0.000000        0.333333

       net_score  slang_score
0      -0.111111    -0.111111
1       0.100000    -0.200000
2       0.142857    -0.285714
3       0.000000    -0.333333
4       0.000000    -0.500000
…          …          …
24995   0.375000    -0.125000
24996   0.059211    -0.125000
24997   0.142857    -0.071429
24998   0.047619    -0.047619
24999  -0.333333     0.333333

[25000 rows x 9 columns]
```

- (optional) Download the "politics_data_slang.csv" for saving the time running the slangSD apply function.

[116]:

```
# politics_data = pd.read_csv("./data/politics_data_slang.csv", encoding='utf8')
```

5.3 ANEW dictionary scoring

- Read in the ANEW dataset and change the variable name of the words.

[118]:
```
anew = pd.read_csv("./data/dict_ANEW.csv")

anew = anew.rename(columns = {"b'Description": "word"})
anew.head()
```

[118]:
```
        word  Word No.  Valence Mean  Valence SD  Arousal Mean  Arousal SD  \
        grin     773.0          7.40        1.87          5.27        2.64
      honest     210.0          7.70        1.43          5.32        1.92
       gripe     774.0          3.14        1.56          5.00        2.19
       honey     792.0          6.73        1.70          4.51        2.25
  guillotine     196.0          2.48        2.11          6.56        2.54

  Dominance Mean  Dominance SD Word Frequency
            6.00          1.86             13
            6.24          2.13             47
            4.67          1.79              .
            5.44          1.47             25
            4.64          2.63              .
```

- Make a new function to calculate the ANEW scores and append to a new variable.

[119]:
```
def anewScorer(text_input, sentiment_list):

    # GET NUMERATOR
    numerator = 0
    for word in str(text_input).split():
        if word in list(sentiment_list):
            numerator += float(anew["Valence Mean"][anew["word"] == word])
        else:
            numerator += 0
    # GET DENOMINATOR
    denominator = len(str(text_input).split())

    # CALCULATE SENTIMENT SCORE
    if denominator == 0:
        sentiment_score = 0
    else:
        sentiment_score = numerator/denominator

    return(sentiment_score)
```

- Run the function through the data set.

[120]:
```
politics_data["anew_score"] = politics_data.apply(lambda x:
                                        anewScorer(x['body'],
                                                   anew["word"]),
                                        axis = 1)
```

5.4 VADER scoring

- Use the nltk package, VADER is designed with a focus on social media texts. Make a new function to calculate the VADER scores and append to a new variable.

[122]:
```
from nltk.sentiment.vader import SentimentIntensityAnalyzer

def vaderScorer(text_input):
    vader = SentimentIntensityAnalyzer()
    output = vader.polarity_scores(str(text_input))['compound']
    return(output)
```

- Apply the vader scorer function to a new variable `vader_score`.

[124]:
```
politics_data["vader_score"] = politics_data["body"].apply(vaderScorer)
```

- Preview data

[125]:
```
politics_data.head(3)
```

[125]:
```
  subreddit                                              body  \
0  politics  yes difference gentle suppression hard suppres…
1  politics  also got married filed jointly husband income …
2  politics  think tell people longer right express themselves

   controversiality  score  body_length  Positive_Score  Negative_Score  \
0                 0      1            9        0.222222        0.333333
1                 0     12           10        0.100000        0.000000
2                 0      1            7        0.142857        0.000000

   net_score  slang_score  anew_score  vader_score
0  -0.111111    -0.111111    2.222222       0.4203
1   0.100000    -0.200000    0.568000       0.1531
2   0.142857    -0.285714    1.047143       0.0000
```

5.5 Normalize the relevant score variables

- Check the summary statistics of the data – the net_score, slang_score, and anew_score variables need to be normalized so that they can be averaged on the same scale.

[126]:
```
politics_data.describe()
```

[126]:
```
       controversiality        score   body_length  Positive_Score  \
count       25000.00000  25000.000000  25000.000000    25000.000000
mean            0.03224     13.809040     18.679800        0.106885
std             0.17664    141.260591     24.571492        0.116847
min             0.00000   -383.000000      0.000000        0.000000
25%             0.00000      1.000000      6.000000        0.000000
50%             0.00000      2.000000     11.000000        0.090909
75%             0.00000      6.000000     22.000000        0.166667
max             1.00000   9715.000000    660.000000        1.000000

       Negative_Score     net_score   slang_score    anew_score   vader_score
count    25000.000000  25000.000000  25000.000000  25000.000000  25000.000000
mean         0.105858      0.001027     -0.053783      0.568576      0.005949
std          0.116204      0.164613      0.146260      0.690321      0.514391
min          0.000000     -1.000000     -1.000000      0.000000     -0.998900
25%          0.000000     -0.071429     -0.121951      0.000000     -0.401900
50%          0.084826      0.000000     -0.015625      0.402500      0.000000
75%          0.166667      0.076923      0.000000      0.860808      0.421500
max          1.000000      1.000000      1.000000      8.100000      0.994300
```

- Standardize variables: Import MinMaxScaler which subtracts the minimum value from each score and divides by the range. This rescales each score from a 0-1 scale. They can then be compared with 0 indicating low valence and 1 indicating high valence.

Reference: https://towardsdatascience.com/scale-standardize-or-normalize-with-scikit-learn-6ccc7d176a02 https://stackoverflow.com/questions/24645153/pandas-dataframe-columns-scaling-with-sklearn

[127]:
```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
politics_data[["net_score",
               "slang_score",
               "anew_score",
               "vader_score"]] = scaler.
 ↪fit_transform(politics_data[["net_score",                                    ␣
 ↪"slang_score",                                                              ␣
 ↪"anew_score",                                                               ␣
 ↪"vader_score"]])
```

- Take the average score and store in a new overall score variable which will be used in the regression.

[128]:
```
politics_data["overall_sent_score"] = (politics_data["net_score"]   +
                                       politics_data["anew_score"]  +
```

```
                                          politics_data["slang_score"] +
                                          politics_data["vader_score"]) / 4
```

- Briefly view the dataset.

[131]:
```
print("Length of data frame: ", len(politics_data))
politics_data.head(3)
```

```
Length of data frame:  25000
```

[131]:
```
  subreddit                                                body  \
0  politics  yes difference gentle suppression hard suppres…
1  politics  also got married filed jointly husband income …
2  politics  think tell people longer right express themselves

   controversiality  score  body_length  Positive_Score  Negative_Score  \
0                 0      1            9        0.222222        0.333333
1                 0     12           10        0.100000        0.000000
2                 0      1            7        0.142857        0.000000

   net_score  slang_score  anew_score  vader_score  overall_sent_score
0   0.444444     0.444444    0.274348     0.712021            0.468815
1   0.550000     0.400000    0.070123     0.577965            0.399522
2   0.571429     0.357143    0.129277     0.501154            0.389751
```

- Descriptive statistics for `overall_sent_score`.

[132]:
```
politics_data["overall_sent_score"].describe()
```

[132]:
```
count    25000.000000
mean         0.386989
std          0.082609
min          0.120641
25%          0.323939
50%          0.381692
75%          0.448989
max          0.814123
Name: overall_sent_score, dtype: float64
```

6 Regression

6.1 Train Multiple Regression on Pandas DF

- Make controversiality a factor variable

[326]:
```
politics_data['controversiality'] = politics_data['controversiality'].
 ↪astype('category')
```

- Find and remove outliers

[327]:
```
# Find IQR
Q1 = politics_data["score"].quantile(0.25)
Q3 = politics_data["score"].quantile(0.75)
IQR = Q3 - Q1

# Remove outliers
politics_out = politics_data[politics_data["score"] < (Q3 + 1.5 * IQR)]
politics_out = politics_out[politics_out["score"] > (Q1 - 1.5 * IQR)]    #␣
↪21461 rows

# Reset Index
politics_out = politics_out.reset_index()
```

- Train/test split

[328]:
```
# Make new df with dependent variables
politics_reg = politics_out[["overall_sent_score", "controversiality",␣
↪"body_length"]]
```

[329]:
```
from sklearn.model_selection import train_test_split

# subset y variable
y = politics_out.score

# split train and test data
X_train, X_test, Y_train, Y_test = train_test_split(politics_reg, y,␣
↪test_size=0.25, random_state = 1)
```

- Fit the model

Reference: https://towardsdatascience.com/train-test-split-and-cross-validation-in-python-80b61beca4b6

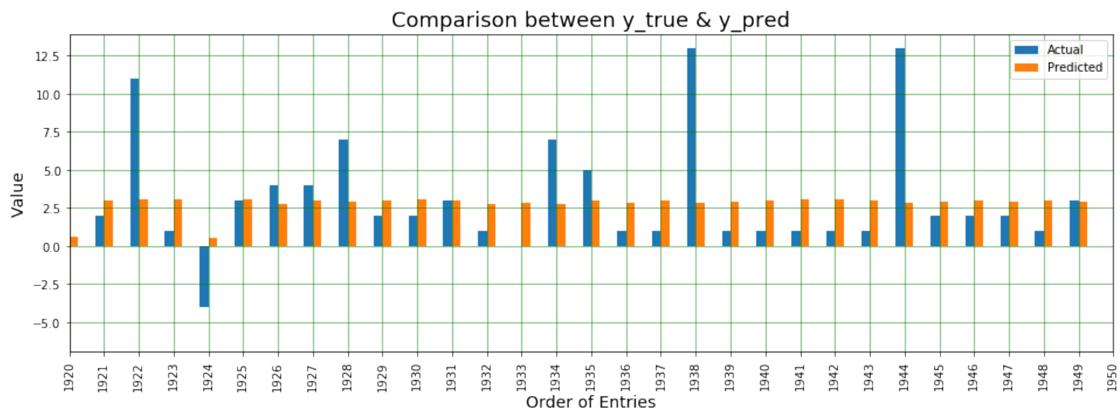
[330]:
```
from sklearn import linear_model
lm = linear_model.LinearRegression()

model = lm.fit(X_train, Y_train)
predictions = lm.predict(X_test)
```

[332]:
```
# create a df
df = pd.DataFrame({'Actual': Y_test, 'Predicted': predictions})
df = df.reset_index(drop = True)

# plotting
plt.figure(figsize = (16, 4))
df.plot(kind = 'bar',figsize = (16,5))
```

```
plt.grid(which = 'major', linestyle = '-', linewidth = '0.5', color = 'green')
plt.grid(which = 'minor', linestyle = ':', linewidth = '0.5', color = 'black')
plt.xlim(1400,1430)
plt.title("Comparison between y_true & y_pred", fontsize = 18)
plt.ylabel("Value", fontsize = 14)
plt.xlabel("Order of Entries", fontsize = 14)

# take a look at part of the data
plt.xlim(1920,1950)
```

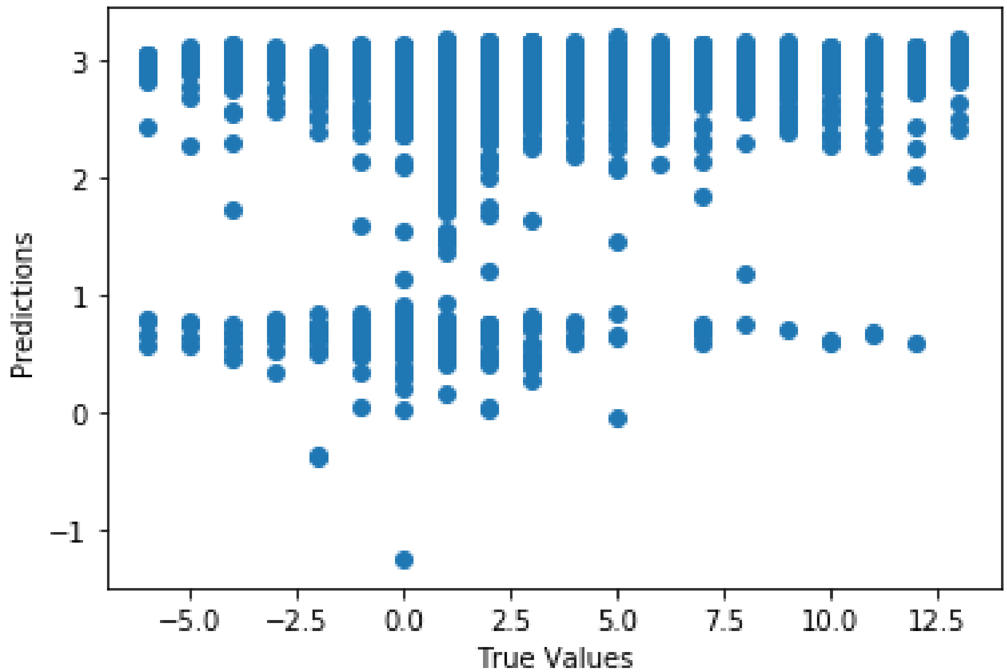
[332]: (1920, 1950)

<Figure size 1152x288 with 0 Axes>



[139]:
```
plt.scatter(Y_test, predictions)
plt.xlabel("True Values")
plt.ylabel("Predictions")
```

[139]: Text(0, 0.5, 'Predictions')



[140]:
```
print("R-squared:", model.score(X_test, Y_test)) # low value
```

```
R-squared: 0.024614384673189327
```

[141]:
```
rmse = 0
for i in range(len(predictions)):

    rmse += (list(Y_test)[i] - predictions[i]) ** 2

    rmse_out = np.sqrt(rmse / len(predictions))

print("RMSE:", rmse_out) # Pretty low
```

```
RMSE: 3.1906255142759106
```

[142]:
```
model.intercept_
```

[142]: 3.355518994093951

[143]:
```
print("Coefficient Values")
print("overall_sent_score:", model.coef_[0])
print("controversiality:", model.coef_[1])
print("body_length:", model.coef_[2])
```

```
Coefficient Values
```

```
overall_sent_score: -0.7711052668422775
controversiality: -2.2835054224168094
body_length: -0.007888327217906
```

6.2 Run general linear regression without splitting to get coefficients

[144]:
```
import statsmodels.formula.api as sm  # import statsmodels
```

- Regress the score of the comment on the length, it's overall sentiment score, and its controversialness.

[145]:
```
results = sm.ols("score ~ body_length + overall_sent_score + controversiality",
                 data = politics_out).fit()
```

- Low R-Squared Value –> statistical significance for all dependent variables.

[290]:
```
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  score   R-squared:                       0.022
Model:                            OLS   Adj. R-squared:                  0.022
Method:                 Least Squares   F-statistic:                     158.9
Date:                Thu, 23 Apr 2020   Prob (F-statistic):          6.71e-102
Time:                        10:57:39   Log-Likelihood:                -55394.
No. Observations:               21461   AIC:                         1.108e+05
Df Residuals:                   21457   BIC:                         1.108e+05
Df Model:                           3
Covariance Type:            nonrobust
================================================================================
=========
                            coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
---------
Intercept                 3.2959      0.105     31.296      0.000       3.090
3.502
controversiality[T.1]    -2.3192      0.118    -19.576      0.000      -2.551
-2.087
body_length              -0.0083      0.001     -9.265      0.000      -0.010
-0.007
overall_sent_score       -0.6039      0.263     -2.300      0.021      -1.119
-0.089
==============================================================================
Omnibus:                     3572.816   Durbin-Watson:                   1.973
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             6124.309
Skew:                           1.094   Prob(JB):                         0.00
Kurtosis:                       4.436   Cond. No.                         396.
```

```
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

- Parameter Results: very similar to train/test split coefficients (6.1).

[147]:
```
results.params  # very very similar to train/test split coefficients
```

[147]:
```
Intercept                   3.295924
controversiality[T.1]      -2.319194
body_length                -0.008282
overall_sent_score         -0.603923
dtype: float64
```

6.3 Train regression model on TF-IDF matrix

- Re-define TF-IDF matrix

[333]:
```
tfidf_vectorizer = TfidfVectorizer(max_df = 0.90, min_df = 10,
                                   ngram_range=(1, 1), stop_words = "english")
X = tfidf_vectorizer.fit_transform(corpus)

X = X.toarray()
tfidf_df = pd.DataFrame(X)
```

- Add score variable

[149]:
```
tfidf_df = tfidf_df.join(politics_data[["score", "body_length",␣
 ↪"overall_sent_score", "controversiality"]])
```

[150]:
```
tfidf_df.head()
```

[150]:
```
     0    1    2    3    4    5    6    7    8    9  …  4100  4101  4102  \
0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  …   0.0   0.0   0.0
1  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  …   0.0   0.0   0.0
2  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  …   0.0   0.0   0.0
3  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  …   0.0   0.0   0.0
4  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  …   0.0   0.0   0.0

   4103  4104  4105  score  body_length  overall_sent_score  controversiality
0   0.0   0.0   0.0      1            9            0.468815                 0
1   0.0   0.0   0.0     12           10            0.399522                 0
2   0.0   0.0   0.0      1            7            0.389751                 0
3   0.0   0.0   0.0     -6            6            0.390280                 0
4   0.0   0.0   0.0     17            6            0.345299                 0

[5 rows x 4110 columns]
```

- Remove outliers, subset y variable, remove score variable.

[151]:
```
# Find IQR
Q1 = tfidf_df["score"].quantile(0.25)
Q3 = tfidf_df["score"].quantile(0.75)
IQR = Q3 - Q1

# Remove outliers
tfidf_out = tfidf_df[tfidf_df["score"] < (Q3 + 1.5 * IQR)]
tfidf_out = tfidf_out[tfidf_out["score"] > (Q1 - 1.5 * IQR)]



# subset y variable
y2 = tfidf_out.score

# drop score
tfidf_out = tfidf_out.drop(columns = ["score"])

# Reset Index
tfidf_out = tfidf_out.reset_index()
```

[152]:
```
tfidf_out.head()
```

[152]:
```
   index    0    1    2    3    4    5    6    7    8  …  4099  4100  4101  \
0      0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  …   0.0   0.0   0.0
1      1  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  …   0.0   0.0   0.0
2      2  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  …   0.0   0.0   0.0
3      3  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  …   0.0   0.0   0.0
4      5  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  …   0.0   0.0   0.0

   4102  4103  4104  4105  body_length  overall_sent_score  controversiality
0   0.0   0.0   0.0   0.0            9            0.468815                 0
1   0.0   0.0   0.0   0.0           10            0.399522                 0
2   0.0   0.0   0.0   0.0            7            0.389751                 0
3   0.0   0.0   0.0   0.0            6            0.390280                 0
4   0.0   0.0   0.0   0.0           12            0.432123                 0

[5 rows x 4110 columns]
```

- Train/test split

[153]:
```
# split train and test data
X2_train, X2_test, Y2_train, Y2_test = train_test_split(tfidf_out, y2,
                                                        test_size = 0.25,␣
 ↪random_state = 1)
```

- Fit a new model

[154]:

```
lm = linear_model.LinearRegression()
model2 = lm.fit(X2_train, Y2_train)
predictions2 = lm.predict(X2_test)
```

- **Produce plots of yhat vs. ytrue:** According to the plots below, the difference between y_pred and y_true is large sometimes but it is pretty close most of the time.

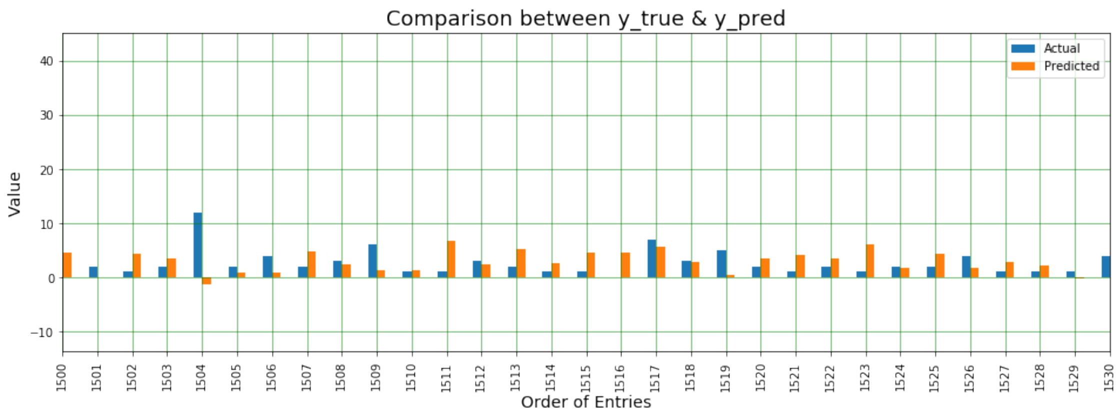
Reference: https://bit.ly/2RT2SRe

[286]:

```
# create a df
df2 = pd.DataFrame({'Actual': Y2_test, 'Predicted': predictions2})
df2 = df.reset_index(drop = True)

# plotting
plt.figure(figsize = (16, 4))
df2.plot(kind = 'bar',figsize = (16,5))
plt.grid(which = 'major', linestyle = '-', linewidth = '0.5', color = 'green')
plt.grid(which = 'minor', linestyle = ':', linewidth = '0.5', color = 'black')
plt.xlim(1400,1430)
plt.title("Comparison between y_true & y_pred", fontsize = 18)
plt.ylabel("Value", fontsize = 14)
plt.xlabel("Order of Entries", fontsize = 14)

# take a look at part of the data
plt.xlim(1500,1530)
```

[286]: (1500, 1530)

```
<Figure size 1152x288 with 0 Axes>
```

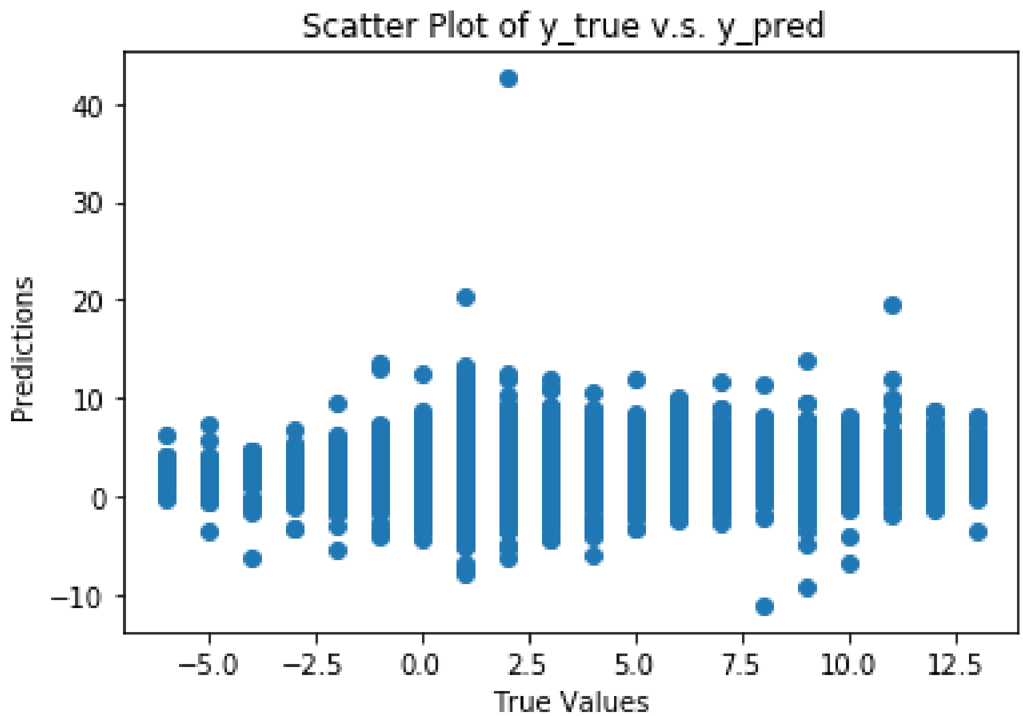


[277]:

```
plt.scatter(Y2_test, predictions2)
plt.title("Scatter Plot of y_true v.s. y_pred")
plt.xlabel("True Values")
```

```
plt.ylabel("Predictions")
```

[277]: Text(0, 0.5, 'Predictions')



- Summary Stats... R-squared not accurate (and negative –> not accurate –>see help page) but RMSE is low.

[157]:
```
print("R-squared:", model2.score(X2_test, Y2_test))
```

R-squared: -0.3442531730282339

[158]:
```
rmse = 0
for i in range(len(predictions2)):

    rmse += (list(Y2_test)[i] - predictions2[i]) ** 2

    rmse_out = np.sqrt(rmse / len(predictions2))

print("RMSE:", rmse_out)
```

RMSE: 3.745658641619775

- Make a dataframe from the coefficient outputs.

[159]:
```python
betas = pd.DataFrame(model2.coef_[1:])
betas.columns = ["Betas"]
```

[184]:
```python
betas.head(10)
```

[184]:
```
      Betas
0 -0.200438
1  1.276361
2  0.062117
3  3.030117
4 -0.700279
5 -0.813882
6  1.415927
7  5.907177
8 -0.846506
9  8.524779
```

- Sort term dictionary by the index that they were in for the TF-IDF matrix.

Reference: https://stackoverflow.com/questions/613183/how-do-i-sort-a-dictionary-by-value

[161]:
```python
terms_dict = {k: v for k, v in sorted(tfidf_vectorizer.vocabulary_.items(),
                                      key = lambda item: item[1])}
terms = pd.DataFrame(list(terms_dict.keys()))
```

[183]:
```python
terms.head(10)
```

[183]:
```
            0
0   abandoned
1     ability
2        able
3    abortion
4      abrams
5    absolute
6  absolutely
7      absurd
8       abuse
9      abused
```

- Join the dictionaries.

[163]:
```python
coefficients = betas.join(terms)
coefficients.columns = ["Betas", "Feature"]
```

- See which 1-gram words had highest/lowest coefficients. There seems to be no discernable pattern.

[164]:
```python
coefficients.sort_values(by = 'Betas', ascending = False).head(7)
```

[164]:

	Betas	Feature
2655	78.391272	performed
2463	62.098451	notability
3416	62.098451	soundclips
2693	35.607651	placed
2020	26.326307	keywords
116	20.087543	alleviate
556	17.381032	cheated

[165]:
```
coefficients.sort_values(by = "Betas", ascending = True).head(7)
```

[165]:

	Betas	Feature
3558	-121.007879	subredditmessagecomposeto
1260	-32.885438	exclusive
681	-27.632830	completing
249	-22.158693	authorize
1096	-19.887569	drama
1415	-17.731639	flooding
1059	-17.497666	division

7 Topic Modeling

- Create and apply a function trimming too long/possibly non-word. Remove words which contain more than 20 characters.

[ ]:
```
# write a function
def vocab_trimmer(docs):

    words = docs.split()
    word_trim = [w for w in words if len(w) < 20 ]

    return(word_trim)

# apply the function for the body variable in politics_data
politics_data["body"] = politics_data["body"].apply(vocab_trimmer)

# make a corpus
corpus = list(politics_data["body"])

# briefly print the corpus
corpus[0:7]
```

7.1 TF-IDF vectorizing

[166]:
```
tfidf_vectorizer = TfidfVectorizer(max_df = 0.90, min_df = 10,
                                   ngram_range=(1, 2), stop_words = "english")
X = tfidf_vectorizer.fit_transform(corpus)
tfidf_vocab = tfidf_vectorizer.get_feature_names()   # vocabulary list (terms)

X.toarray()   # term-freq matrix_At
```

[166]:
```
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]])
```

[167]:
```
np.shape(X.toarray())   # 25,000 documents * 5,920 vocabulary
```

[167]:
```
(25000, 5877)
```

7.2 NMF on TF-IDF matrix

[168]:
```
### NMF

# function for returning output
def print_top_words(model, vocab_list, n_top_words):
    for topic_idx, topic in enumerate(model.components_):
        message = "Topic #%d: " % topic_idx
        message += " ".join([vocab_list[i]
                             for i in topic.argsort()[:-n_top_words - 1:-1]])
        output = print(message)
    return(output)

# NMF results - 10 topics with top 20 words
nmf = NMF(n_components = 10).fit(X)
print_top_words(nmf, tfidf_vocab, n_top_words = 20)
```

```
Topic #0: violation rule automatically subredditmessagecomposeto question
performed automatically action performed bot action contact moderator moderator
subredditmessagecomposeto subredditmessagecomposeto automatically contact
question concern performed report bot ban comment harm rule rule violation
wishing deathphysical advocating wishing comment violation
Topic #1: people right republican know time want vote thing going need good make
way democrat really point sure year mean let
Topic #2: submission removal regarding removal regarding question removal
submission thank removed megathread feel free removal feel moderator regarding
question removal free message thank participating question regarding message
```

```
moderator participating message free
Topic #3: barr mueller said letter summary congress medium doj mueller said
report testify thought inaccurate official memo mueller letter mueller report
lied testimony coverage
Topic #4: like look look like sound sound like feel like feel barr look like
trump like barr guy people like post lol lot act act like eye thing like thing
Topic #5: trump president supporter trump supporter biden donald obstruction
donald trump crime justice evidence russia election investigation campaign like
trump russian impeachment collusion trump campaign
Topic #6: public letter investigation department context summary counsel special
special counsel substance nature substance context nature nature work capture
conclusion capture context released march fully
Topic #7: read report say read report obstruction mueller report collusion
article president report say justice evidence page lol mueller read article
crime thing redacted saying
Topic #8: graham lindsey lindsey graham shit fucking fuck email hillary fucking
idiot idiot lindsay clinton lindsay graham lol talking piece shit piece trump
fucking hearing holy
Topic #9: think really think barr got people think think trump make guy wrong
think going happen going tell really think job think mueller actually reason
think mean lol
```

8 KMeans Clustering

- Import kmeans module

[302]:
```
from sklearn.cluster import KMeans
```

- Subsetted data to test on

[303]:
```
test = politics_data.sample(5000)
test_list = list(test["body"])
```

- Get TF-IDF and H Matrix (for clustering and topic output).

[304]:
```
X = tfidf_vectorizer.fit_transform(corpus)
H = nmf.fit_transform(X)
vocab = tfidf_vectorizer.get_feature_names()
```

- Write a function to get top 10 words which are the nearset to the centroids.

Reference: http://brandonrose.org/clustering#Tf-idf-and-document-similarity

[305]:
```
## Top n words for each cluster
def top_words_KM(cluster, n_top_words, vocab_list):

    # get centroids and arrange the indices of centroids
    order_centroids_index = cluster.cluster_centers_.argsort()[:,::-1]
```

```
    for i in range(cluster.n_clusters):
        print_wds = [vocab_list[index] for index in order_centroids_index[i,:
↪n_top_words]]
        output = print("Cluster {}: {}".format(i, ', '.join(print_wds)))

    return(output)
```

[306]:
```
KM = KMeans(n_clusters = 10, random_state = 1, max_iter = 100)
kmeans_label = KM.fit_predict(X).tolist()
top_words_KM(cluster = KM, n_top_words = 15, vocab_list = vocab)
```

```
Cluster 0: right, graham, shit, fucking, lindsey, lindsey graham, trump, fuck,
like, thing, piece shit, know, piece, going, email
Cluster 1: submission, removal, regarding removal, regarding, removal
submission, question, thank, removed, megathread, removal feel, free message,
moderator regarding, question removal, thank participating, question regarding
Cluster 2: people, republican, vote, trump, like, think, want, democrat, thing,
know, party, need, right, make, american
Cluster 3: violation, rule, shill troll, attack idea, general courteous,
personal insult, troll accusation, accusation hate, advocating wishing, result
permanent, permanent ban, subreddit civil, ban comment, violation result, speech
advocating
Cluster 4: mueller, barr, letter, said, doj, report, summary, congress, mueller
said, medium, mueller letter, say, investigation, testify, know
Cluster 5: trump, like, think, know, say, going, need, want, make, president,
thing, way, really, mean, got
Cluster 6: barr, trump, like, summary, letter, report, congress, mueller, going,
think, know, tomorrow, lie, said, testimony
Cluster 7: good, good thing, thing, luck, good luck, trump, guy, make, like,
know, think, bad, right, point, really
Cluster 8: time, trump, like, think, going, people, actually, right, thing,
know, year, need, barr, long, vote
Cluster 9: report, read, mueller, summary, obstruction, read report, mueller
report, public, counsel, letter, special counsel, special, context,
investigation, conclusion
```

- Get the counts of the cluster assignments.

[307]:
```
from collections import Counter
Counter(kmeans_label) # one cluster has most of the comments (seems like the␣
↪most general too)
```

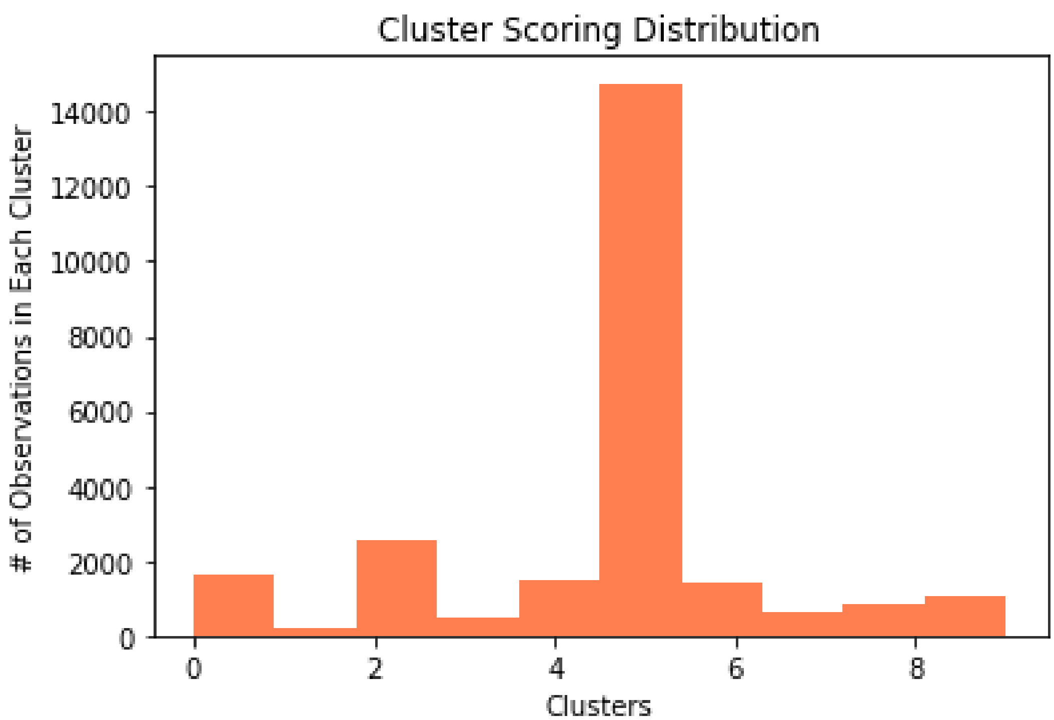
[307]:
```
Counter({7: 614,
         5: 14756,
         2: 2537,
         4: 1479,
         3: 469,
         9: 1070,
```

```
6: 1399,
1: 231,
8: 840,
0: 1605})
```

- Plot a histogram of the cluster assignments.

[325]:
```
plt.hist(kmeans_label, color = "coral")
plt.xlabel("Clusters")
plt.ylabel("# of Observations in Each Cluster")
plt.title("Cluster Scoring Distribution")
```

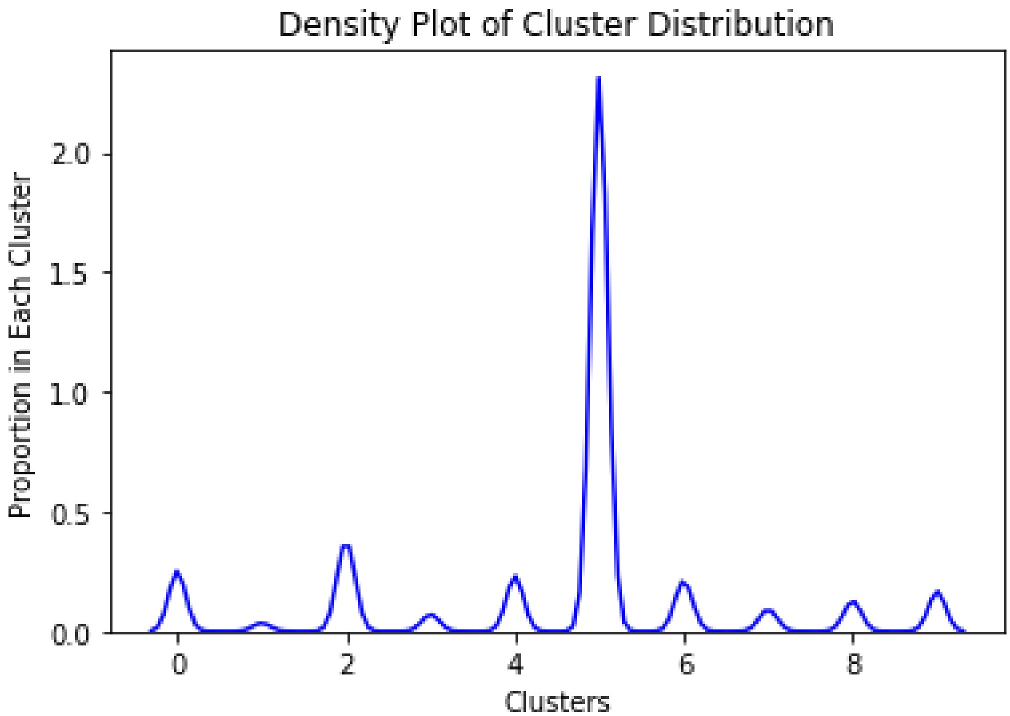
[325]:
```
Text(0.5, 1.0, 'Cluster Scoring Distribution')
```



- Plot a density plot of the cluster assignments.

[309]:
```
sns.distplot(kmeans_label, hist = False, color= "blue", bins = 1)
plt.title("Density Plot of Cluster Distribution")
plt.xlabel("Clusters")
plt.ylabel("Proportion in Each Cluster")
```

[309]:
```
Text(0, 0.5, 'Proportion in Each Cluster')
```



- Check text of comments to see if they are similar.

[320]:
```
my_list = []
for i in range(len(kmeans_label)):
    if kmeans_label[i] == 5:
        my_list.append(i)

print(my_list[0:10])
print(my_list[145:155])
print(my_list[-10:-1])
```

```
[1, 4, 5, 7, 9, 11, 12, 14, 15, 20]
[242, 243, 246, 247, 248, 249, 252, 253, 254, 259]
[24982, 24984, 24985, 24987, 24990, 24992, 24993, 24994, 24996]
```

- Pick a few index numbers from directly above and replace in code below to see similar output. The clusters seem to line up.

[324]:
```
print("1.", politics_data["body"][5])

print("2", politics_data["body"][243])

print("3",politics_data["body"][24992])
```

```
1. everything power make sure biden get nomination fall line doe primary
```

```
coronation
2 nope nonstate function dignitary conducting diplomacy actual state function
govt funded kind event actually considered government business reimbursed thus
trump pr move buying hamberders shutdown save government intended save him
billionaire money
3 well corporation democrat pocket case trump make cut
```

9 Classification

9.1 Two classes - sports subreddits

- We wanted to pick subreddits that were similar enough to be tough to train a model on but distinct enough to tell differences. Sports themes subreddits seemed to fit the model.

[197]:
```python
# Re-load original data
data = data
```

- Import packages

[198]:
```python
# classifying modules
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import RidgeClassifier

# sklearn
from sklearn.metrics import classification_report
from sklearn.metrics import f1_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
```

- Subset data

[199]:
```python
subs = ["nba", "nfl"]
test = data[data.subreddit.isin(subs)]
```

- Clean data

[200]:
```python
test["body"] = test["body"].apply(textCleaner)
test["body"] = test["body"].apply(textNormalization)
test["body"]
```

[200]:
```
7                                            report water wet
12                                 michael jackson popcorn gif
23         the reason anyone know jared dudley ben simmon…
31         would say year old buddy hield part king young…
55                                  oh know going comment lol
                                   …
919444     mean put weight letter lawyer nfl gtfinally m …
919445                    rip fedora man really getting good
919449     andy reid marv levy suffer lack super bowl alt…
```

```
919456    none change fact succeeded nfl point star play…
919486    mean reason season great last year oline stren…
Name: body, Length: 50000, dtype: object
```

- Define and run classifier function

[201]:
```
def isNBA(string):
    x = 0
    if string == "nba":
        x += 1
    return(x)

test["category"] = test.subreddit.apply(isNBA)
```

[203]:
```
test.head()
```

[203]:
```
   subreddit                                               body  \
7        nba                                    report water wet
12       nba                          michael jackson popcorn gif
23       nba  the reason anyone know jared dudley ben simmon…
31       nba  would say year old buddy hield part king young…
55       nba                            oh know going comment lol

    controversiality  score  category
7                  0      9         1
12                 0      1         1
23                 0     -5         1
31                 1     -2         1
55                 0      1         1
```

- Make corpus for vectorization and y_true tags.

[204]:
```
text = list(test["body"])
classifier = list(test["category"])
```

- Split and vectorize the data

[205]:
```
data_train, data_test = train_test_split(text, train_size = 0.8, random_state =␣
 ↪5)
y_train, y_actual = train_test_split(classifier, train_size = 0.8, random_state␣
 ↪= 5)
```

[206]:
```
X_train = tfidf_vectorizer.fit_transform(data_train)
H_train = nmf.fit_transform(X_train)
```

- Fit Knn classfier

[207]:
```
neigh = KNeighborsClassifier(n_neighbors = 4)
neigh.fit(H_train, y_train)
```

[207]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=4, p=2,
                     weights='uniform')
```

- Generate predicted classes

[208]:
```
X_test = tfidf_vectorizer.transform(data_test) # not fit
H_test = nmf.transform(X_test) # not fit
```

[209]:
```
y_pred = neigh.predict(H_test)
```

- Get classifier scores. This model is overall a pretty accurate model.

[210]:
```
print("F1 Score:", f1_score(y_actual, y_pred))
print("Precision Score:", precision_score(y_actual, y_pred))
print("Recall Score:", recall_score(y_actual, y_pred))
```

```
F1 Score: 0.6695862625331336
Precision Score: 0.7911220043572985
Recall Score: 0.5804195804195804
```

[211]:
```
target_names = ["NBA", "NFL"]
print(classification_report(y_actual, y_pred, target_names = target_names))
```

```
              precision    recall  f1-score   support

         NBA       0.67      0.85      0.75      4995
         NFL       0.79      0.58      0.67      5005

    accuracy                           0.71     10000
   macro avg       0.73      0.71      0.71     10000
weighted avg       0.73      0.71      0.71     10000
```

9.2 Four classes - More sports

- According to the classification results below, it is tougher to train more classes.

[212]:
```
data = data
```

[213]:
```
subs = ["nba", "nfl", "hockey", "soccer"]
test = data[data.subreddit.isin(subs)]
```

[214]:
```
test["body"] = test["body"].apply(textCleaner)
test["body"] = test["body"].apply(textNormalization)
```

```
test["body"]
```

[214]:
```
7                                               report water wet
12                                  michael jackson popcorn gif
21                               google chrome suck donkey dick
23         the reason anyone know jared dudley ben simmon…
31         would say year old buddy hield part king young…
                                  …
919444     mean put weight letter lawyer nfl gtfinally m …
919445                     rip fedora man really getting good
919449     andy reid marv levy suffer lack super bowl alt…
919456     none change fact succeeded nfl point star play…
919486     mean reason season great last year oline stren…
Name: body, Length: 100000, dtype: object
```

[215]:
```
def isNBA(string):
    x = 0
    if string == "nba":
        x = 0
    elif string == "nfl":
        x = 1
    elif string == "hockey":
        x = 2
    elif string == "soccer":
        x = 3
    return(x)

test["category"] = test.subreddit.apply(isNBA)
```

[216]:
```
test
```

[216]:
```
       subreddit                                               body  \
7            nba                                report water wet
12           nba                     michael jackson popcorn gif
21        hockey                  google chrome suck donkey dick
23           nba  the reason anyone know jared dudley ben simmon…
31           nba  would say year old buddy hield part king young…
…          …                                                …
919444       nfl  mean put weight letter lawyer nfl gtfinally m …
919445       nfl               rip fedora man really getting good
919449       nfl  andy reid marv levy suffer lack super bowl alt…
919456       nfl  none change fact succeeded nfl point star play…
919486       nfl  mean reason season great last year oline stren…

        controversiality  score  category
7                      0      9         0
12                     0      1         0
```

```
21                          0      2          2
23                          0     -5          0
31                          1     -2          0
…                       …     …       …
919444                      0      0          1
919445                      0      4          1
919449                      0      7          1
919456                      0      4          1
919486                      0     11          1

[100000 rows x 5 columns]
```

[217]:
```
text = list(test["body"])
classifier = list(test["category"])
```

[218]:
```
data_train, data_test = train_test_split(text, train_size = 0.8, random_state =␣
↪5)
y_train, y_actual = train_test_split(classifier, train_size = 0.8, random_state␣
↪= 5)
```

[219]:
```
X_train = tfidf_vectorizer.fit_transform(data_train)
H_train = nmf.fit_transform(X_train)
```

[220]:
```
neigh = KNeighborsClassifier(n_neighbors = 4)
neigh.fit(H_train, y_train)
```

[220]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=4, p=2,
                     weights='uniform')
```

[221]:
```
X_test = tfidf_vectorizer.transform(data_test) # not fit
H_test = nmf.transform(X_test) # not fit
```

[222]:
```
y_pred = neigh.predict(H_test)
```

[223]:
```
f1_score(y_actual, y_pred, average="weighted")
```

[223]:
```
0.3836387209725444
```

[224]:
```
precision_score(y_actual, y_pred, average="weighted")
```

[224]:
```
0.3886078659789782
```

[225]:
```
recall_score(y_actual, y_pred, average = "weighted")
```

[225]:
```
0.38765
```

- The output gives a less accurate model, but still not that bad.

[226]:
```
target_names = ["NBA", "NFL", "Hockey", "Soccer"]
print(classification_report(y_actual, y_pred, target_names = target_names))
```

```
              precision    recall  f1-score   support

         NBA       0.41      0.51      0.46      5003
         NFL       0.36      0.42      0.39      4921
      Hockey       0.35      0.29      0.32      5011
      Soccer       0.43      0.33      0.37      5065

    accuracy                           0.39     20000
   macro avg       0.39      0.39      0.38     20000
weighted avg       0.39      0.39      0.38     20000
```

10 Appendix

10.1 Bindary Logistic Regression

- As we can see from the counts & graph below, the percentage of controversiality is 96.776, and the percentage of no controversiality is 3.22399. The controversiality is unbalanced.

Reference https://towardsdatascience.com/building-a-logistic-regression-in-python-step-by-step-becd4d56c9c8

[243]:
```
politics_data["controversiality"].value_counts()[1]
```

[243]:
```
806
```

[244]:
```
# see the counts of controversiality
print("Value counts of controversiality:")
print(politics_data["controversiality"].value_counts())
```

```
Value counts of controversiality:
0    24194
1      806
Name: controversiality, dtype: int64
```

- If we look at the mean of score and sentiment scores groupby controversiality, the average score of up reddits minus down reddits has discrepancy (2.9 v.s. 0.58). However, the mean in all sentiment scores as well as overall sentiment score are all pretty close in between. Even the overall score has 0.01 higher in controversiality then no controversiality.

[245]:
```
politics_out.groupby("controversiality").mean()
```

[245]:
```
                         index     score  body_length  Positive_Score  \
controversiality
```

```
0                   12485.650826  2.908529    18.535642        0.108551
1                   12918.679470  0.582781    18.998675        0.108177

                    Negative_Score  net_score  slang_score  anew_score  \
controversiality
0                         0.106273   0.501139     0.472363    0.070580
1                         0.106746   0.500716     0.472868    0.071179

                    vader_score  overall_sent_score
controversiality
0                      0.505058            0.387285
1                      0.522387            0.391787
```

- Implement the model. The p-values are small (< 0.05).

[255]:
```python
import statsmodels.api as sm
# subset y variable
x = politics_out[["overall_sent_score", "score"]]
y = politics_out.controversiality

# Logit model
logit_model = sm.Logit(y, x)
result = logit_model.fit()

# ------------- print result -------------
# p-value < 0.05 (both score & overall_sent_score)
result.summary2()
```

```
Optimization terminated successfully.
         Current function value: 0.147881
         Iterations 8
```

[255]:
```
<class 'statsmodels.iolib.summary2.Summary'>
"""
                          Results: Logit
==================================================================
Model:              Logit            Pseudo R-squared: 0.029
Dependent Variable: controversiality AIC:              6351.3343
Date:               2020-04-23 04:58 BIC:              6367.2822
No. Observations:   21461            Log-Likelihood:   -3173.7
Df Model:           1                LL-Null:          -3268.8
Df Residuals:       21459            LLR p-value:      2.9149e-43
Converged:          1.0000           Scale:            1.0000
No. Iterations:     8.0000
------------------------------------------------------------------
                    Coef.  Std.Err.    z     P>|z|   [0.025  0.975]
------------------------------------------------------------------
```

```
overall_sent_score -7.1376   0.1050 -67.9966 0.0000 -7.3433 -6.9319
score              -0.3505   0.0152 -23.0740 0.0000 -0.3803 -0.3208
===================================================================

"""
```

- Continually try on Logistic Regression Model Fitting.

[256]:
```python
from sklearn import linear_model
from sklearn import metrics

X_train, X_test, y_train, y_test = train_test_split(x, y,
                                                    test_size = 0.25,␣
 ↪random_state = 1)
lm = linear_model.LogisticRegression()
model = lm.fit(X_train, Y_train)
predictions = lm.predict(X_test)

# ------------- print result -------------
print("Intercept:", model.intercept_)
print("RMSE:", np.sqrt(metrics.mean_squared_error(y_test, predictions)))
```

```
Intercept: [ -7.69446842  -5.76404902  -4.89978361  -5.11096805  -3.74612598
  -3.54537763  -2.3821199    0.60505876  -1.40963169  -2.33395375
  -3.11511531  -3.5133533   -3.98212319  -4.42548451  -5.30640502
  -6.13031765  -6.5206707   -7.84194941  -9.34061325 -13.52020389]
RMSE: 2.80211437127095
```

- **Accuracy (R-squared)**: The accuracy of logistic regression classifier on test set is 0.96 (very high).

[257]:
```python
print("R-squared:", model.score(X_test, y_test))
```

```
R-squared: 0.034103615355594484
```

- **Confusion Matrix**: The result gives that we have [5168 + 0] correct predictions and [198 + 0] incorrect predictions.

[258]:
```python
from sklearn.metrics import confusion_matrix

confusion_matrix = confusion_matrix(y_test, predictions)
print(confusion_matrix)
```

```
[[   0 3963  501  306   77   49  110   25   17  120]
 [   0  183    4    5    1    0    4    0    0    1]
 [   0    0    0    0    0    0    0    0    0    0]
 [   0    0    0    0    0    0    0    0    0    0]
 [   0    0    0    0    0    0    0    0    0    0]
 [   0    0    0    0    0    0    0    0    0    0]
```

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

Precision, recall, F-measure and support

The precision not to label classifier positive if it's negative. The recall helps to find all positive samples, in this data result, we have most non-controversiality samples. Lastly, the f1-score gives an overall mean to evaluate precision and recall. The support returns the number of occurrences of each class in y_test.

According to the report below and the unbalanved controversiality rate, the precision and recall are both high (precision = 96%, recall = 100%), though the f1-score = 98% is almost the best. I believe this data is overfitting. Of the entire dataset, 98% reviews are non-controversiality.

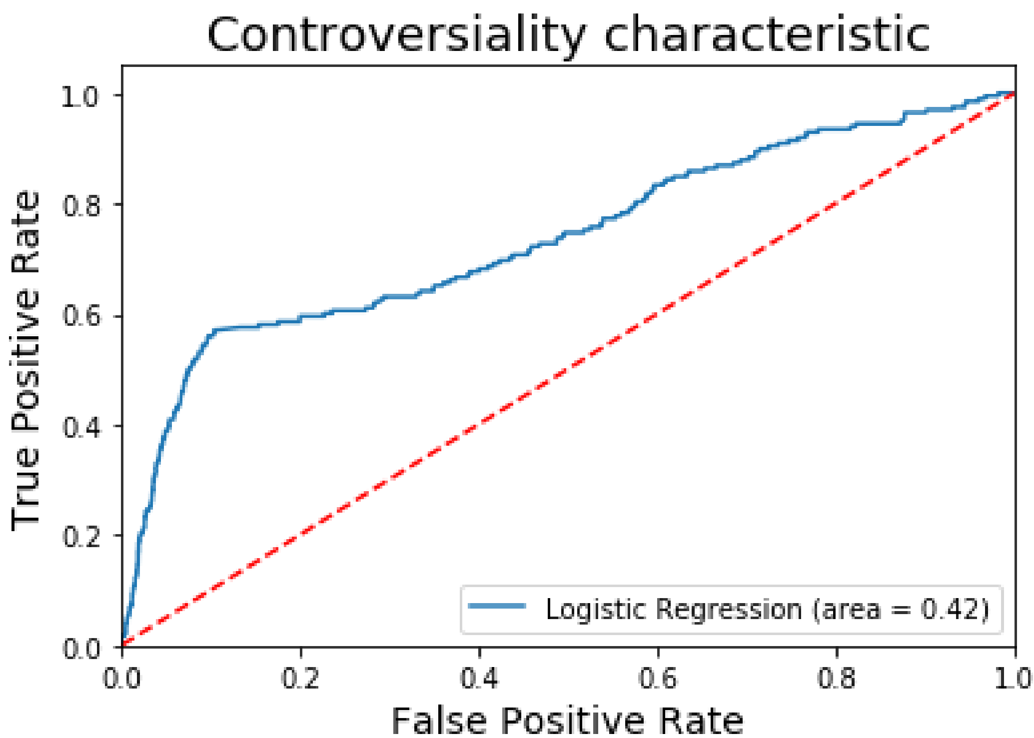
[253]:
```
from sklearn.metrics import classification_report

print(classification_report(y_test, predictions))
```

```
              precision    recall  f1-score   support

           0       0.00      0.00      0.00      5168
           1       0.04      0.92      0.08       198
           2       0.00      0.00      0.00         0
           3       0.00      0.00      0.00         0
           5       0.00      0.00      0.00         0
           6       0.00      0.00      0.00         0
           7       0.00      0.00      0.00         0
           9       0.00      0.00      0.00         0
          10       0.00      0.00      0.00         0
          13       0.00      0.00      0.00         0

    accuracy                           0.03      5366
   macro avg       0.00      0.09      0.01      5366
weighted avg       0.00      0.03      0.00      5366
```

ROC Curve

[254]:
```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve

logit_roc_auc = roc_auc_score(y_test, predictions)
fpr, tpr, thresholds = roc_curve(y_test, lm.predict_proba(X_test)[:,1])

plt.figure()
plt.plot(fpr, tpr, label = 'Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
```

```
plt.ylim([0.0, 1.05])
plt.title('Controversiality characteristic', fontsize = 18)
plt.xlabel('False Positive Rate', fontsize = 14)
plt.ylabel('True Positive Rate', fontsize = 14)
plt.legend(loc = "lower right")
plt.savefig('Log_ROC')
plt.show()
```



10.1.1 /Additional Work/

- We tried to create a visual graph of the clusters; however, this proved to be too difficult. To do this, we found that we needed to convert each document to a 2D form so it could be plotted on a flat plane. The computing power to do this on the entire dataset and produce coherant output was very difficult. The output graph below was with 5,000 of the 25,000 observations, and the online source we were trying to work through was difficult to apply to our project. We ultimately felt it was best to leave it out.

10.2 Multidimensional Scaling

- Using multidimensional scaling to convert the dist matrix into a 2-dimensional array.

Reference: http://brandonrose.org/clustering#Tf-idf-and-document-similarity*

- Get cosine distance

[227]:
```
from sklearn.metrics.pairwise import cosine_similarity
dist = 1 - cosine_similarity(X)
```

- Import packages

[228]:
```
import matplotlib as mpl
from sklearn.manifold import MDS
```

[229]:
```
# convert two components as we're plotting points in a two-dimensional plane
# "precomputed" because we provide a distance matrix
MDS()
mds = MDS(n_components = 2, dissimilarity = "precomputed", random_state = 1,␣
↪max_iter = 100)
```

- The transform function below for mds() takes a very very long while running through it.

[347]:
```
# [!] takes a while
pos = mds.fit_transform(dist)   # shape (n_components, n_samples)
xs, ys = pos[:, 0], pos[:, 1]
```

[306]:
```
# create a dataframe
cluster_df = pd.DataFrame(dict(x = xs, y = ys,
                               label = kmeans_label,
                               score = list(test["score"])))   # should be␣
↪title = titles
# group by clusters
groups = cluster_df.groupby('label')
```

[230]:
```
# set up colors per clusters using a dict
cluster_colors = {0: 'red', 1: 'blue', 2: 'green', 3: 'purple', 4: 'orange', 5:␣
↪'brown'}

#set up cluster names using a dict
cluster_names = {0: 'republican, Trump, democrat',
                 1: 'justice, Mueller report, congress',
                 2: 'violation, harm',
                 3: 'thoughts, feelings',
                 4: 'say, Trump, action',
                 5: 'submission, removal'}
```

[308]:
```
# set output plot size
fig, ax = plt.subplots(figsize = (17, 9)) # set size
ax.margins(0.05)

# iterate through groups to layer the plot
for name, group in groups:
    ax.plot(group.x, group.y, marker = 'o', linestyle = '', ms = 12,
```

```
            label = cluster_names[name], color = cluster_colors[name],
            mec = 'none')
    ax.set_aspect('auto')
    ax.tick_params(\
        axis = 'x',          # changes apply to the x-axis
        which = 'both',      # both major and minor ticks are affected
        bottom = 'off',      # ticks along the bottom edge are off
        top = 'off',         # ticks along the top edge are off
        labelbottom = 'off')
    ax.tick_params(\
        axis = 'y',         # changes apply to the y-axis
        which = 'both',      # both major and minor ticks are affected
        left = 'off',      # ticks along the bottom edge are off
        top = 'off',         # ticks along the top edge are off
        labelleft = 'off')

ax.legend(numpoints = 1)

# add labels
for i in range(len(cluster_df)):
    ax.text(cluster_df.iloc[i]['x'],
            cluster_df.iloc[i]['y'],
            cluster_df.iloc[i]['score'], size = 9)

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