AIT_Project_Midsemester

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1 AIT Project - Mid Semester Evaluation

Alan Gaugler
U885853
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This version uses a Naive-Bayes model with Tf-Idf and word2vec. Results are poor on the 42 classes.

The best Naive-Bayes model achieved an accuracy of 57.8% using bag of words.
The Logistic Regression model achieved an accuracy of 60.5% using a Tf-idf vectorizer.

Text preparation is place into one function.

2 Introduction

This project is concerned with article classification. A news category dataset with over 200,000 article headlines and descriptions will be used in this project. The aim is to read and interpret the headlines and descriptions and categorize them into one of 42 topic categories.

Import the required libraries

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
from collections import Counter

import re
import string
from gensim.models import Phrases
from gensim.models.phrases import Phraser

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import classification_report, f1_score, accuracy_score,␣
↪confusion_matrix
```

```python
from sklearn.metrics import roc_curve, auc, roc_auc_score
from sklearn.feature_extraction.text import TfidfVectorizer

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

2.0.1 Exploratory Data Analysis

[2]:
```python
# Load the JSON file
df = pd.read_json("News_Category_Dataset_v3.json", lines=True)
```

[3]:
```python
# Display the header
df.head()
```

[3]:
```
                                                link  \
0  https://www.huffpost.com/entry/covid-boosters-…
1  https://www.huffpost.com/entry/american-airlin…
2  https://www.huffpost.com/entry/funniest-tweets…
3  https://www.huffpost.com/entry/funniest-parent…
4  https://www.huffpost.com/entry/amy-cooper-lose…

                                            headline   category  \
0  Over 4 Million Americans Roll Up Sleeves For O…  U.S. NEWS
1  American Airlines Flyer Charged, Banned For Li…  U.S. NEWS
2  23 Of The Funniest Tweets About Cats And Dogs …     COMEDY
3  The Funniest Tweets From Parents This Week (Se…  PARENTING
4  Woman Who Called Cops On Black Bird-Watcher Lo…  U.S. NEWS

                                   short_description               authors  \
0  Health experts said it is too early to predict…  Carla K. Johnson, AP
1  He was subdued by passengers and crew when he …        Mary Papenfuss
2  "Until you have a dog you don't understand wha…         Elyse Wanshel
3  "Accidentally put grown-up toothpaste on my to…      Caroline Bologna
4  Amy Cooper accused investment firm Franklin Te…        Nina Golgowski

        date
0 2022-09-23
1 2022-09-23
2 2022-09-23
3 2022-09-23
4 2022-09-22
```

The dataset consists of 6 columns:

link: The URL of the news article. **headline:** The headline of the article. **category:** The category of type or article. This is the target variable. **short_description:** A short description of the article. This will be key in identyfying the article category. **authours:** The names of the article's authours. **date:** The date of the article's publication.

[4]:
```python
df.shape
```

[4]:
```
(209527, 6)
```

This is a large dataset with 209527 articles.

[5]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 209527 entries, 0 to 209526
Data columns (total 6 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   link               209527 non-null  object
 1   headline           209527 non-null  object
 2   category           209527 non-null  object
 3   short_description  209527 non-null  object
 4   authors            209527 non-null  object
 5   date               209527 non-null  datetime64[ns]
dtypes: datetime64[ns](1), object(5)
memory usage: 9.6+ MB
```

All columns are objects except for the date which is datetime.

[6]:
```python
df.describe()
```

```
C:\Users\alang\AppData\Local\Temp\ipykernel_46288\3627053830.py:1:
FutureWarning: Treating datetime data as categorical rather than numeric in
`.describe` is deprecated and will be removed in a future version of pandas.
Specify `datetime_is_numeric=True` to silence this warning and adopt the future
behavior now.
  df.describe()
```

[6]:
```
                                                     link        headline  \
count                                              209527          209527
unique                                             209486          207996
top     https://www.huffingtonpost.comhttps://www.wash…  Sunday Roundup
freq                                                    2              90
first                                                 NaN             NaN
last                                                  NaN             NaN

        category short_description authors                 date
count     209527            209527  209527               209527
unique        42            187022   29169                 3890
top     POLITICS                             2014-03-25 00:00:00
freq       35602             19712   37418                  100
first        NaN               NaN     NaN  2012-01-28 00:00:00
last         NaN               NaN     NaN  2022-09-23 00:00:00
```

[7]:
```python
# Find the number of missing values in each column
df.isna().sum()
```

[7]:
```
link                 0
headline             0
category             0
short_description    0
authors              0
date                 0
dtype: int64
```

There are no missing values in the dataset.

[8]:
```python
# Are there any duplicate headlines?
df['headline'].value_counts()
```

[8]:
```
Sunday Roundup
90
The 20 Funniest Tweets From Women This Week
80
Weekly Roundup of eBay Vintage Clothing Finds (PHOTOS)
59
Weekly Roundup of eBay Vintage Home Finds (PHOTOS)
54
Watch The Top 9 YouTube Videos Of The Week
46
..
Here Are The Manufacturers Bringing The Most Jobs Back to America
1
2016 Campaigns Meet With White House To Prep For Obama's Last Days In Office
1
If Toddlers Could Calmly Articulate Their Feelings
1
Snapchat's Bob Marley Filter Called Out For Being 'Digital Blackface'
1
Dwight Howard Rips Teammates After Magic Loss To Hornets
1
Name: headline, Length: 207996, dtype: int64
```

Yes. There are many headlines that are duplicates. They all appear to be weekly articles.

[9]:
```python
# Are there any duplicate short descriptions?
df['short_description'].value_counts()
```

[9]:
```
                                                  19712
Welcome to the HuffPost Rise Morning Newsbrief, a short wrap-up of the news to
help you start your day.                                     192
The stress and strain of constantly being connected can sometimes take your life
```

```
-- and your well-being -- off course. GPS         125
Want more? Be sure to check out HuffPost Style on Twitter, Facebook, Tumblr,
Pinterest and Instagram at @HuffPostStyle. -- Do       91
Do you have a home story idea or tip? Email us at
homesubmissions@huffingtonpost.com. (PR pitches sent to this address will
75
                                                  …
The "Selma" director is teaming up with Oprah for her first ever TV series.
1
It's one of the thorniest moral dilemmas in tech right now.
1
The new addition to the family will be a little sibling the to the couple's two
adopted children.                                    1
This old hymn has often been used as an anthem for freedom.
1
The five-time all-star center tore into his teammates Friday night after Orlando
committed 23 turnovers en route to losing           1
Name: short_description, Length: 187022, dtype: int64
```

There are duplicate short descriptions.
The headline and the short description columns will be merged togther for the analysis
This will reduce the number of duplicates.

[10]:
```python
# Display all the categories
df['category'].unique()
```

[10]:
```
array(['U.S. NEWS', 'COMEDY', 'PARENTING', 'WORLD NEWS', 'CULTURE & ARTS',
       'TECH', 'SPORTS', 'ENTERTAINMENT', 'POLITICS', 'WEIRD NEWS',
       'ENVIRONMENT', 'EDUCATION', 'CRIME', 'SCIENCE', 'WELLNESS',
       'BUSINESS', 'STYLE & BEAUTY', 'FOOD & DRINK', 'MEDIA',
       'QUEER VOICES', 'HOME & LIVING', 'WOMEN', 'BLACK VOICES', 'TRAVEL',
       'MONEY', 'RELIGION', 'LATINO VOICES', 'IMPACT', 'WEDDINGS',
       'COLLEGE', 'PARENTS', 'ARTS & CULTURE', 'STYLE', 'GREEN', 'TASTE',
       'HEALTHY LIVING', 'THE WORLDPOST', 'GOOD NEWS', 'WORLDPOST',
       'FIFTY', 'ARTS', 'DIVORCE'], dtype=object)
```

[11]:
```python
df['category'].nunique()
```

[11]:
```
42
```

There are 42 unique values. These will be the categories.

[12]:
```python
# Display the number of articles per category
df['category'].value_counts()
```

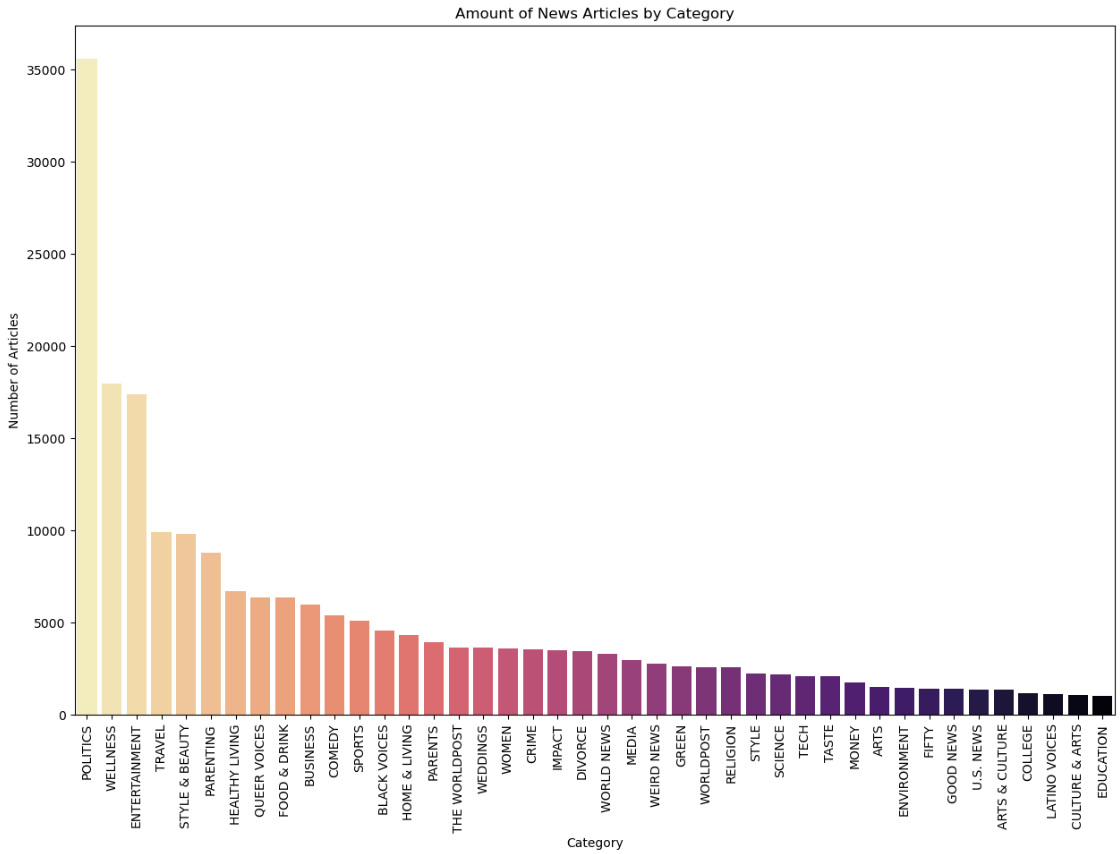
[12]:
```
POLITICS          35602
WELLNESS          17945
ENTERTAINMENT     17362
```

```
TRAVEL            9900
STYLE & BEAUTY    9814
PARENTING         8791
HEALTHY LIVING    6694
QUEER VOICES      6347
FOOD & DRINK      6340
BUSINESS          5992
COMEDY            5400
SPORTS            5077
BLACK VOICES      4583
HOME & LIVING     4320
PARENTS           3955
THE WORLDPOST     3664
WEDDINGS          3653
WOMEN             3572
CRIME             3562
IMPACT            3484
DIVORCE           3426
WORLD NEWS        3299
MEDIA             2944
WEIRD NEWS        2777
GREEN             2622
WORLDPOST         2579
RELIGION          2577
STYLE             2254
SCIENCE           2206
TECH              2104
TASTE             2096
MONEY             1756
ARTS              1509
ENVIRONMENT       1444
FIFTY             1401
GOOD NEWS         1398
U.S. NEWS         1377
ARTS & CULTURE    1339
COLLEGE           1144
LATINO VOICES     1130
CULTURE & ARTS    1074
EDUCATION         1014
Name: category, dtype: int64
```

[13]:

```
# Plot the distribution of news articles by news category.
plt.figure(figsize=(15, 10))
ax = sns.countplot(x=df['category'], order=df['category'].value_counts().index,␣
 ↪palette="magma_r")
plt.title('Amount of News Articles by Category')
plt.ylabel('Number of Articles')
```

```
plt.xlabel('Category')
plt.xticks(rotation=90)
plt.show()
```

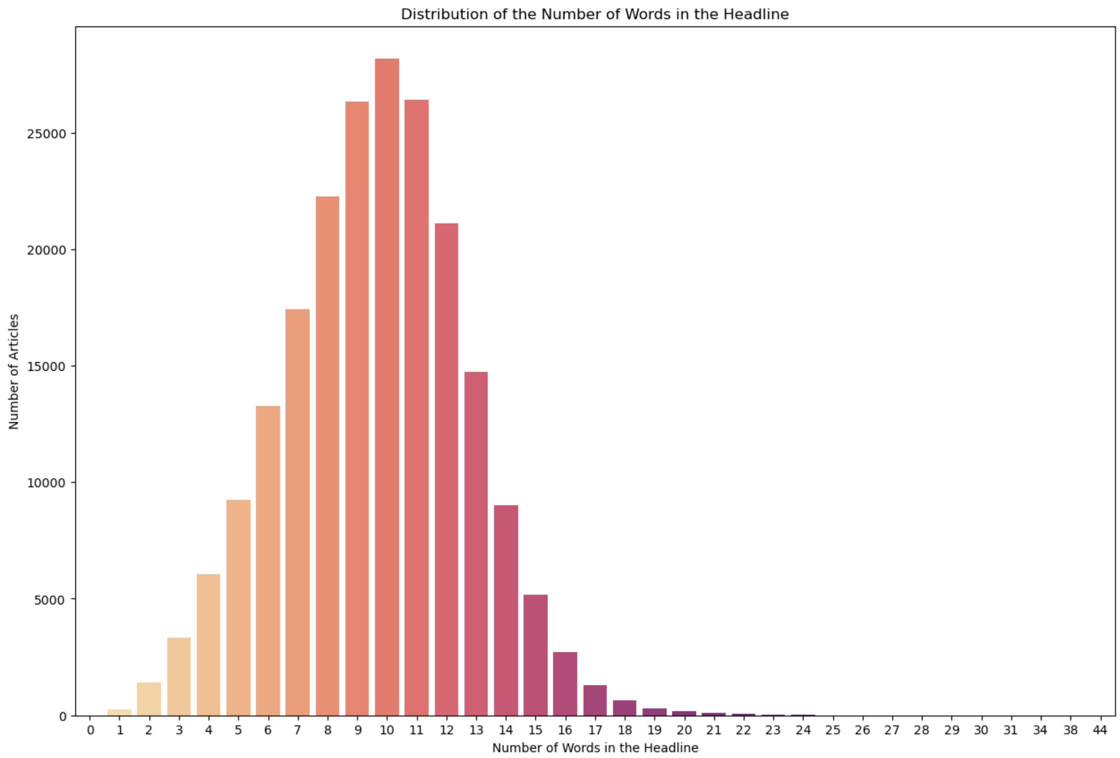


Politics is by far the most common category in this dataset, followed by wellness and entertainment. This dataset is clearly very imbalanced. This will produce challenges in predicting the minority categories.

[14]:
```
# Add extra columns to count the number of words in the headline and the short␣
↪description
df['word_count_headline'] = df['headline'].apply(lambda text: len(str(text).
↪split()))
df['word_count_description'] = df['short_description'].apply(lambda text:␣
↪len(str(text).split()))
```

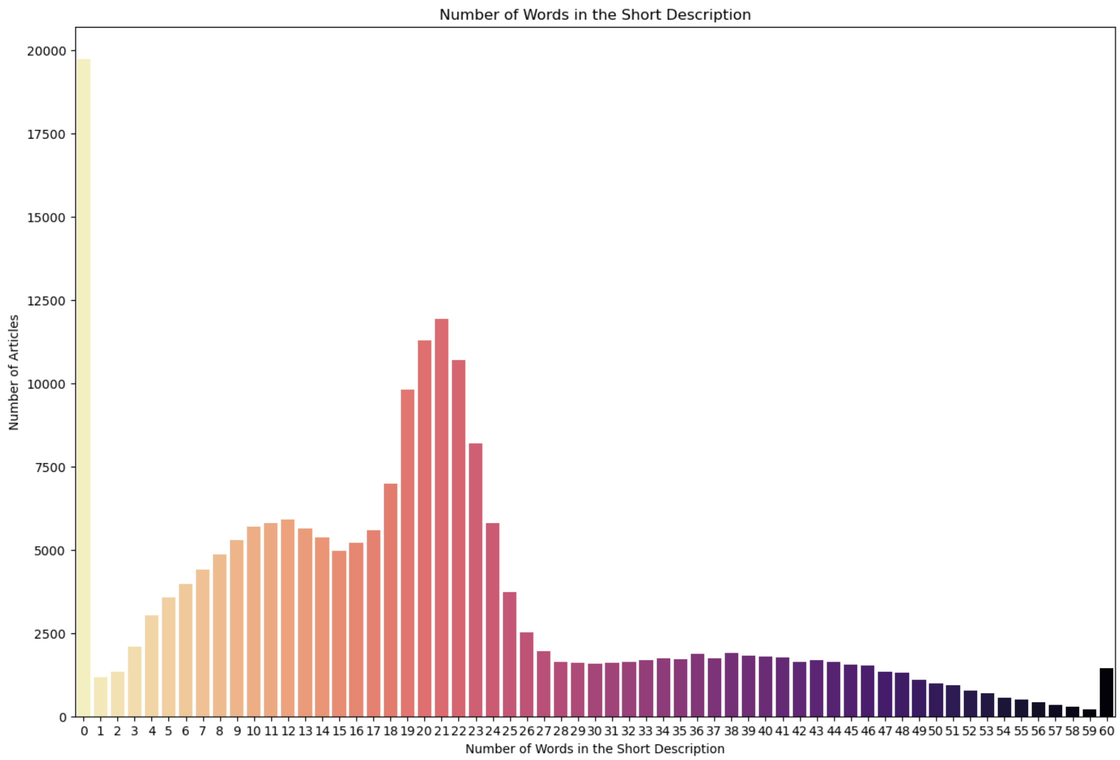
[15]:
```
# Plot the Distribution of the Number of Words in the Headline.
plt.figure(figsize=(15, 10))
ax = sns.countplot(x=df['word_count_headline'],
                   order=df['word_count_headline'].value_counts().
↪sort_index(ascending=True).index,
```

```
                   palette="magma_r")
plt.title('Distribution of the Number of Words in the Headline')
plt.ylabel('Number of Articles')
plt.xlabel('Number of Words in the Headline')
plt.show()
```



The number of words per headline has a fairly normalized distribution, centered on 10 words.

[16]:
```
# Plot the Distribution of the Number of Words in the Short Description.
capped_word_count = df['word_count_description'].apply(lambda x: 60 if x >= 60␣
 ↪else x)

plt.figure(figsize=(15, 10))
ax = sns.countplot(x=capped_word_count,
                   order=capped_word_count.value_counts().
 ↪sort_index(ascending=True).index,
                   palette="magma_r")
plt.title('Number of Words in the Short Description')
plt.ylabel('Number of Articles')
plt.xlabel('Number of Words in the Short Description')
plt.show()
```



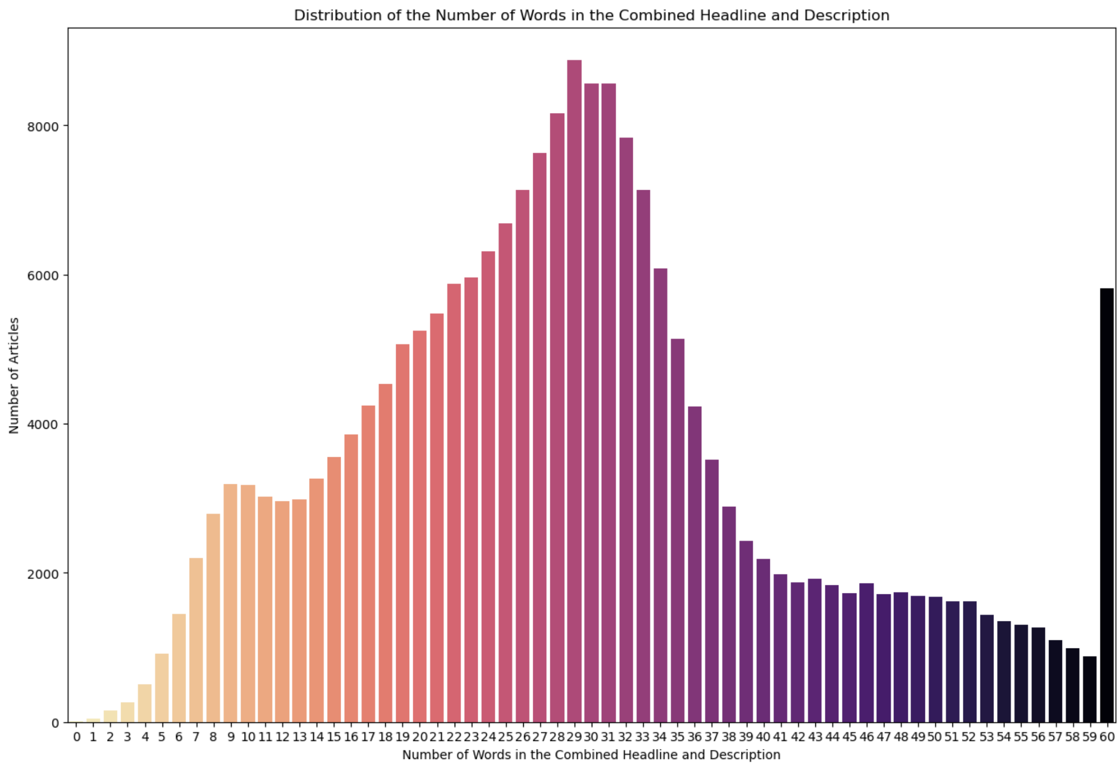
Looking at the plot above, there are 19712 articles in this dataset that do not have a description, but rather just a headline. The number 60 is actually 60+. This has been capped for this plot only but not for the actual dataset. The distribution of the number of words in the short description interestingly has 3 peaks. The first peak is at 12 words, the largest peak is at 21 words and the smallest is at 38 words. This distribution is definitely not normal. It will be investigated to see if there is any correlation between the category and the word length of the short description.

There are 19712 articles that have no description and 6 that have no headline. To get a more complete view of the article, the headline and the short description will be merged together into a new feature called 'combined_information'.

[17]:
```
# Create a new feature that concatenates 'headline' and 'short_description'.
df['combined_info'] = df['headline'].str.strip() + ' ' +␣
↪df['short_description'].str.strip()

# Create an extra column to count the number of words in the combined_info␣
↪feature.
df['word_count_combined'] = df['combined_info'].apply(lambda text:␣
↪len(str(text).split()))
```

[18]:
```
# Plot the Distribution of the Number of Words in the Short Description.
capped_combined_count = df['word_count_combined'].apply(lambda x: 60 if x >= 60␣
↪else x)
```

```
# Plot the Distribution of the Number of Words in the Combined Information.
plt.figure(figsize=(15, 10))
ax = sns.countplot(x=capped_combined_count,
                   order=capped_combined_count.value_counts().
 ↪sort_index(ascending=True).index,
                   palette="magma_r")
plt.title('Distribution of the Number of Words in the Combined Headline and␣
 ↪Description')
plt.ylabel('Number of Articles')
plt.xlabel('Number of Words in the Combined Headline and Description')
plt.show()
```



The peak of the combined word distribution is centred on 29 words. The number 60 is actually 60+. This has been capped for this plot only but not for the actual dataset.

[19]:
```
# Are there any duplicates in the combined info column?
df['combined_info'].value_counts()
```

[19]:
```
Watch The Top 9 YouTube Videos Of The Week If you're looking to see the most
popular YouTube videos of the week, look no further. Once again, we're bringing
you the                                                  46
The Funniest Tweets From Women This Week
```

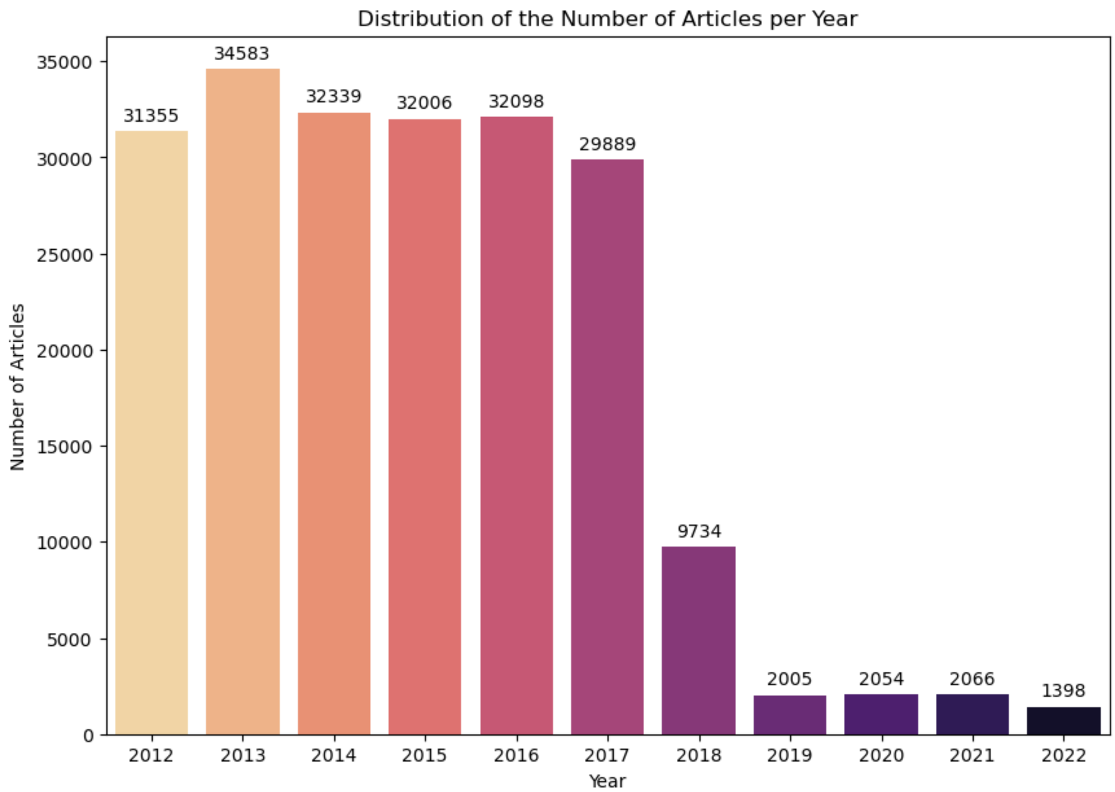
```
33
The 20 Funniest Tweets From Women This Week The ladies of Twitter never fail to
brighten our days with their brilliant   but succinct   wisdom. Each week,
HuffPost Women                                      30
Best Parenting Tweets: What Moms And Dads Said On Twitter This Week Kids may say
the darndest things, but parents tweet about them in the funniest ways. So each
week, we round up the most hilarious        26
Funniest Parenting Tweets: What Moms And Dads Said On Twitter This Week Kids may
say the darndest things, but parents tweet about them in the funniest ways. So
each week, we round up the most hilarious    23
                                             ..
It Just Got Harder For LA Police To Confiscate Homeless People's Possessions
Cops often fail to distinguish between contaminated property and that which is
essential for homeless people to survive.         1
English Town Builds Shrine For Cookies Dropped On Street "I first saw them at
around 10 p.m. and felt the twinge of sympathy natural for such a horrible
scene."                                              1
Serena Williams Takes Badass To New Levels In He-Man Costume So, so fierce.
1
Duke University Urges Repeal Of North Carolina's Anti-Trans Law The renowned
university says HB 2 is causing prospective students and professors to avoid its
campus.                                          1
Dwight Howard Rips Teammates After Magic Loss To Hornets The five-time all-star
center tore into his teammates Friday night after Orlando committed 23 turnovers
en route to losing                           1
Name: combined_info, Length: 209038, dtype: int64
```

There are still duplicates in the 'combined_info' column, but this number has been reduced to just 46. 46 out of 209,527 is extremely low and will not bias the results significantly. These are articles that were actually published, so they will not be removed from this project.

[20]:
```python
# Create new columns for the year and month of publication.
df['year'] = pd.to_datetime(df['date']).dt.year
df['month'] = pd.to_datetime(df['date']).dt.month
```

[21]:
```python
# Plot the Distribution of the Number of Articles per Year.
plt.figure(figsize=(10, 7))
ax = sns.countplot(x=df['year'],
                   order=df['year'].value_counts().sort_index().index,
                   palette="magma_r")
plt.title('Distribution of the Number of Articles per Year')
plt.ylabel('Number of Articles')
plt.xlabel('Year')

# Add the numerical quantity at the top of each bar
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x() + p.get_width()/2,  # get X coordinate + width / 2
```

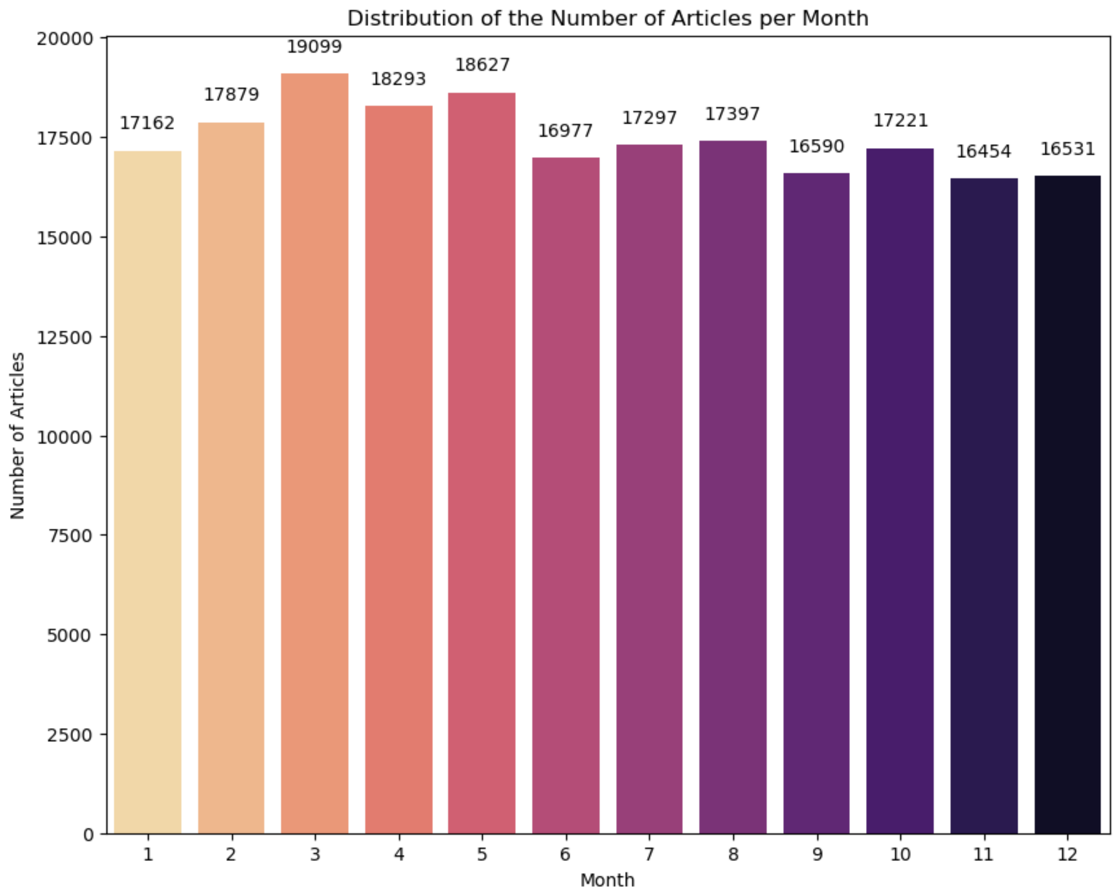
```
            height + 550,  # set the text slightly above the bar
            '{:1.0f}'.format(height),
            ha="center")

plt.show()
```



The original dataset was made in June 2018, when a roughly even amount of articles were collected from 2012 to May 2018. Since then, there have been updates to the dataset but not as many new articles were collected.

[22]:
```
# Plot the Distribution of the Number of Articles per Month.
plt.figure(figsize=(10,8))
ax = sns.countplot(x=df['month'],
                   order=df['month'].value_counts().sort_index().index,
                   palette="magma_r")
plt.title('Distribution of the Number of Articles per Month')
plt.ylabel('Number of Articles')
plt.xlabel('Month')

# Add the numerical quantity at the top of each bar
for p in ax.patches:
    height = p.get_height()
```

```
    ax.text(p.get_x() + p.get_width()/2,  # get X coordinate + width / 2
            height + 550,  # set the text slightly above the bar
            '{:1.0f}'.format(height),
            ha="center")

plt.show()
```



The number of articles distributed per month is relatively even. The busiest month is March with 19099 and the quietest are November and December at around 16500. These months are during the holiday period in the US and more journalists may be taking time off.

[23]:
```
df.describe()
```

[23]:
```
       word_count_headline  word_count_description  word_count_combined  \
count        209527.000000           209527.000000        209527.000000
mean              9.600744               19.669026            29.269770
std               3.068507               14.152783            13.803927
min               0.000000                0.000000             0.000000
25%               8.000000               10.000000            20.000000
```

```
50%              10.000000              19.000000             28.000000
75%              12.000000              24.000000             35.000000
max              44.000000             243.000000            245.000000

                year          month
count  209527.000000  209527.000000
mean     2014.837634       6.393100
std         2.087349       3.429701
min      2012.000000       1.000000
25%      2013.000000       3.000000
50%      2015.000000       6.000000
75%      2016.000000       9.000000
max      2022.000000      12.000000
```

[24]:

```python
# Observe if any 'combined_info' column is empty or contains just one word.
df[df['word_count_combined'] <= 1].head(10)
```

[24]:

```
                                                    link       headline  \
63714  https://www.huffingtonpost.com/entry/manscrapi…  "ManScraping"
66196  https://www.huffingtonpost.com/entry/tire-d_b_…        Tire-d
66203  https://www.huffingtonpost.com/entry/wafflewic…     Wafflewich
72366  https://www.huffingtonpost.com/entry/hangman_b…       Hangman
78481  https://www.huffingtonpost.com/entry/hugs_b_89…          Hugs
81477  https://www.huffingtonpost.com/entry/memories_…      Memories
81496  https://www.huffingtonpost.com/entry/what-to-d…       IGNORE.
82119  https://www.huffingtonpost.com/entry/podcast_b…       Podcast
86508  https://www.huffingtonpost.com/entry/the-ideal…         Once.
90944  https://www.huffingtonpost.com/entry/lincoln-2…

      category short_description  \
63714   COMEDY
66196   COMEDY
66203    TASTE
72366   COMEDY
78481   COMEDY
81477   COMEDY
81496 POLITICS
82119   COMEDY
86508   COMEDY
90944 POLITICS

                                                 authors       date  \
63714          Tom Kramer, ContributorWriter of the Wry 2016-06-26
66196  Marcia Liss, Contributor(Almost) Famous Cartoo… 2016-05-29
66203  Dough Mamma, ContributorPrivate chef, culinary… 2016-05-29
72366  Marcia Liss, Contributor(Almost) Famous Cartoo… 2016-03-19
78481  Marcia Liss, Contributor(Almost) Famous Cartoo… 2016-01-10
```

```
81477  Marcia Liss, Contributor(Almost) Famous Cartoo… 2015-12-06
81496  Gabriela Rivera-Morales, ContributorBlog Edito… 2015-12-06
82119  Marcia Liss, Contributor(Almost) Famous Cartoo… 2015-11-29
86508  Marcia Liss, Contributor(Almost) Famous Cartoo… 2015-10-11
90944  Robert Moran, ContributorRobert Moran leads Br… 2015-08-22

       word_count_headline  word_count_description   combined_info  \
63714                    1                       0  "ManScraping"
66196                    1                       0         Tire-d
66203                    1                       0     Wafflewich
72366                    1                       0        Hangman
78481                    1                       0           Hugs
81477                    1                       0       Memories
81496                    1                       0        IGNORE.
82119                    1                       0        Podcast
86508                    1                       0          Once.
90944                    0                       0

       word_count_combined  year  month
63714                    1  2016      6
66196                    1  2016      5
66203                    1  2016      5
72366                    1  2016      3
78481                    1  2016      1
81477                    1  2015     12
81496                    1  2015     12
82119                    1  2015     11
86508                    1  2015     10
90944                    0  2015      8
```

[25]:
```python
len(df[df['word_count_combined'] <= 1])
```

[25]:
```
53
```

Five rows were found to not have any textual information at all in the 'combined info' column. If this column is empty, no information can be conveyed into what category it belongs to. One word is also too little information to accurately classify the topic. These rows will be removed.

[26]:
```python
df = df[df['word_count_combined'] > 1].copy()
```

[27]:
```python
df.shape
```

[27]:
```
(209474, 12)
```

2.1 Feature Engineering / Data Preparation

2.1.1 Text Cleaning and Preprocessing

To prepare the data for natural language processing (NLP), several steps will need to be taken:

1. Text Cleaning - The preprocessing step will convert the text to lowercase, strip and remove punctuations, effectively cleaning the text for further processing.
2. Expand contractions - Contracted words are converted into two words which make more sense. Also, the apostrophes will be removed. An example of this is: "I'd" –> "I would". Many of these words will be removed by the stop word removal step.

3. Tokenization - Partition the text into individual words and symbols. These are called tokens.
4. Stop word removal - This will remove common words that convey no meaning about the article such as "he", "she" or "on".
5. Stemming - This reduces words to their root form i.e., "shows", "showing" and "showed" will be reduced to "show".
6. Lemmatization - This also reduces words to their root form i.e., "better" and "best" will be reduced to "good". This is similar to stemming but the root words are more often real words used in English rather than just their stems.

7. Bigrams and trigrams - Many words often connected in sequence may have a different meaning and should be joined together such as "New" followed by "York" really conveys the meaning of a city called "New York" and they should be considered one word.
8. Removal of unique words - Unique words or words that occur only one time in the entire dataset will be removed. As these words are unique, they will not be encountered in the test set if they are in the training set and so will not convey any information in identifying the topic category. This will also reduce the "noise" in the dataset and speed up processing.

The Natural Language Toolkit (NLTK) and Gensim libraries will be used for this project.

[28]:
```
import nltk
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer, WordNetLemmatizer
from sklearn.feature_extraction.text import TfidfVectorizer
```

[29]:
```
from nltk.tokenize import word_tokenize, sent_tokenize
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer, WordNetLemmatizer

import gensim
from gensim.models import Word2Vec
```

[30]:
```
# Install the necessary NLTK datasets if they are not in the environment yet.
# nltk.download('punkt')
# nltk.download('stopwords')
# nltk.download('wordnet')
```

[31]:
```
# Define the English language stopwords.
stop_words = set(stopwords.words('english'))

# Load the stemmer and lemmatizer
stemmer = PorterStemmer()
lemmatizer = WordNetLemmatizer()
```

[32]:
```
# Display the English stopwords in the NLTK library
print(stop_words)
```

```
{"aren't", 's', "you've", 'isn', 'doesn', 'itself', 'if', 'the', 'doing',
'under', 'his', "couldn't", 'not', 'wouldn', 'in', 'how', 'mustn', 'a', 'whom',
'again', 'weren', 'down', 'hasn', 'were', 'won', 'mightn', 'she', 'her', 'few',
'or', 'did', "haven't", 'be', 'you', 'm', 'themselves', 'on', 'too', 'is', 'am',
'our', "weren't", 'nor', "won't", 'are', 'o', 'only', 'these', 'don',
"should've", 'during', 'from', 'have', 'shan', 'they', 'there', 'but', 'and',
'once', 'yourself', 'wasn', "mightn't", 'very', 'has', 'hadn', "you're", 'this',
"shouldn't", 'further', "wasn't", 'up', "isn't", 'was', 'where', 'now', 'below',
'as', 'does', 'my', 'i', 'me', 'what', 'between', 'having', 'had', 'your',
'such', 'ain', 'it', 'who', 'after', 'been', 'just', "shan't", 'y', "that'll",
"needn't", 'will', 'ours', 'over', 'no', 're', 'with', 'because', 'an', 'both',
'each', "she's", "you'd", 'any', 'some', "hadn't", 'll', 'why', 'against',
'than', 'ma', 'yourselves', 'd', 'here', 'him', 'most', 'off', 'herself', 'of',
've', 'above', "doesn't", 'their', "hasn't", 'shouldn', 'being', 'those', 'by',
'myself', 'so', 'own', "wouldn't", 'for', 'ourselves', 'through', "didn't",
'he', 'didn', 'himself', 'then', 'should', 'yours', "you'll", 'haven', 'aren',
'until', 'all', "it's", 'can', 'more', 'that', 'at', 'other', 'them', "don't",
'out', 'about', 'theirs', 'do', 'before', 'needn', 'couldn', 't', 'hers', 'its',
'to', 'we', 'when', 'which', 'into', 'while', "mustn't", 'same'}
```

[33]:
```
len(stop_words)
```

[33]:
```
179
```

NLTK's English stopwords library contains 179 words.

[34]:
```
df.dtypes
```

[34]:
```
link                              object
headline                          object
category                          object
short_description                 object
authors                           object
date                      datetime64[ns]
word_count_headline                int64
word_count_description             int64
combined_info                     object
word_count_combined                int64
year                               int64
month                              int64
dtype: object
```

[35]:
```
# Make a contractions map:
# A contraction map will convert contracted words into two words
# which make more sense. Also, the apostrophes will be removed.
```

```python
# Credit: This contraction map was obtained from the following source:
# https://github.com/dipanjanS/practical-machine-learning-with-python/blob/
↪master/bonus%20content/nlp%20proven%20approach/contractions.py

CONTRACTION_MAP = {
"ain't": "is not",
"aren't": "are not",
"can't": "cannot",
"can't've": "cannot have",
"'cause": "because",
"could've": "could have",
"couldn't": "could not",
"couldn't've": "could not have",
"didn't": "did not",
"doesn't": "does not",
"don't": "do not",
"hadn't": "had not",
"hadn't've": "had not have",
"hasn't": "has not",
"haven't": "have not",
"he'd": "he would",
"he'd've": "he would have",
"he'll": "he will",
"he'll've": "he he will have",
"he's": "he is",
"how'd": "how did",
"how'd'y": "how do you",
"how'll": "how will",
"how's": "how is",
"I'd": "I would",
"I'd've": "I would have",
"I'll": "I will",
"I'll've": "I will have",
"I'm": "I am",
"I've": "I have",
"i'd": "i would",
"i'd've": "i would have",
"i'll": "i will",
"i'll've": "i will have",
"i'm": "i am",
"i've": "i have",
"isn't": "is not",
"it'd": "it would",
"it'd've": "it would have",
"it'll": "it will",
"it'll've": "it will have",
"it's": "it is",
```

```
"let's": "let us",
"ma'am": "madam",
"mayn't": "may not",
"might've": "might have",
"mightn't": "might not",
"mightn't've": "might not have",
"must've": "must have",
"mustn't": "must not",
"mustn't've": "must not have",
"needn't": "need not",
"needn't've": "need not have",
"o'clock": "of the clock",
"oughtn't": "ought not",
"oughtn't've": "ought not have",
"shan't": "shall not",
"sha'n't": "shall not",
"shan't've": "shall not have",
"she'd": "she would",
"she'd've": "she would have",
"she'll": "she will",
"she'll've": "she will have",
"she's": "she is",
"should've": "should have",
"shouldn't": "should not",
"shouldn't've": "should not have",
"so've": "so have",
"so's": "so as",
"that'd": "that would",
"that'd've": "that would have",
"that's": "that is",
"there'd": "there would",
"there'd've": "there would have",
"there's": "there is",
"they'd": "they would",
"they'd've": "they would have",
"they'll": "they will",
"they'll've": "they will have",
"they're": "they are",
"they've": "they have",
"to've": "to have",
"wasn't": "was not",
"we'd": "we would",
"we'd've": "we would have",
"we'll": "we will",
"we'll've": "we will have",
"we're": "we are",
"we've": "we have",
```

```
"weren't": "were not",
"what'll": "what will",
"what'll've": "what will have",
"what're": "what are",
"what's": "what is",
"what've": "what have",
"when's": "when is",
"when've": "when have",
"where'd": "where did",
"where's": "where is",
"where've": "where have",
"who'll": "who will",
"who'll've": "who will have",
"who's": "who is",
"who've": "who have",
"why's": "why is",
"why've": "why have",
"will've": "will have",
"won't": "will not",
"won't've": "will not have",
"would've": "would have",
"wouldn't": "would not",
"wouldn't've": "would not have",
"y'all": "you all",
"y'all'd": "you all would",
"y'all'd've": "you all would have",
"y'all're": "you all are",
"y'all've": "you all have",
"you'd": "you would",
"you'd've": "you would have",
"you'll": "you will",
"you'll've": "you will have",
"you're": "you are",
"you've": "you have"
}
```

[36]:

```
# Credit: This function to expand contractions was obtained from the following␣
↪source:
# https://www.kdnuggets.com/2018/08/
↪practitioners-guide-processing-understanding-text-2.html
def expand_contractions(text, contraction_mapping=CONTRACTION_MAP):

    contractions_pattern = re.compile('({})'.format('|'.
↪join(contraction_mapping.keys())),
                                      flags=re.IGNORECASE|re.DOTALL)
    def expand_match(contraction):
        match = contraction.group(0)
```

```
        first_char = match[0]
        expanded_contraction = contraction_mapping.get(match)\
                                if contraction_mapping.get(match)\
                                else contraction_mapping.get(match.lower())
        expanded_contraction = first_char+expanded_contraction[1:]
        return expanded_contraction

    expanded_text = contractions_pattern.sub(expand_match, text)
    expanded_text = re.sub("'", "", expanded_text)
    return expanded_text
```

[37]:

```
# Credit: The processing text function shown below is based on code found at␣
↪the following source:
# Reference: https://medium.com/analytics-vidhya/
↪nlp-tutorial-for-text-classification-in-python-8f19cd17b49e
# The preprocessing step will convert the text to lowercase, strip and remove␣
↪punctuations
# effectively cleaning the text for further processing.

def preprocess_text(text):
    # Convert the text to lowercase
    text = text.lower()
    # Call the expand contractions function
    # It was found that this led to a minore decreae in model performance so it␣
↪has been commented out.
    #text = expand_contractions(text)
    # Remove any leading or trailing whitespace.
    text = text.strip()
    # Remove any HTML tags from the text
    text = re.compile('<.*?>').sub('', text)
    # Replace any punctuation with a space
    text = re.compile('[%s]' % re.escape(string.punctuation)).sub(' ', text)
    # Remove any square-bracketed numbers (like [10], [23], etc.)
    text = re.sub(r'\[[0-9]*\]', ' ', text)
    # Remove any non-alphanumeric characters (excluding spaces)
    text = re.sub(r'[^\w\s]', '', str(text).lower().strip())
    # Replace multiple spaces with a single space
    text = re.sub(r'\s+', ' ', text)
    return text
```

[38]:

```
# Create a wordcloud for the desired column
def plot_word_cloud(lemmatized_words, col_name):
    # Combine all the words into one list instead of a list of lists
    word_list = [word for sublist in lemmatized_words for word in sublist]

    # Combine all the words into one large text
    text = ' '.join(word_list)
```

```
    # Create the word cloud object
    wc = WordCloud(width=800, height=800, colormap='Spectral',␣
↪background_color='black',
                   stopwords=set('english'), max_words=200,␣
↪contour_color='black')

    # Generate the word cloud
    wc.generate(text)

    # Display the word cloud
    plt.figure(figsize=(8, 8))
    plt.imshow(wc, interpolation='bilinear')
    plt.axis('off')
    plt.title(f'Word Cloud for {col_name}')
    plt.show()
```

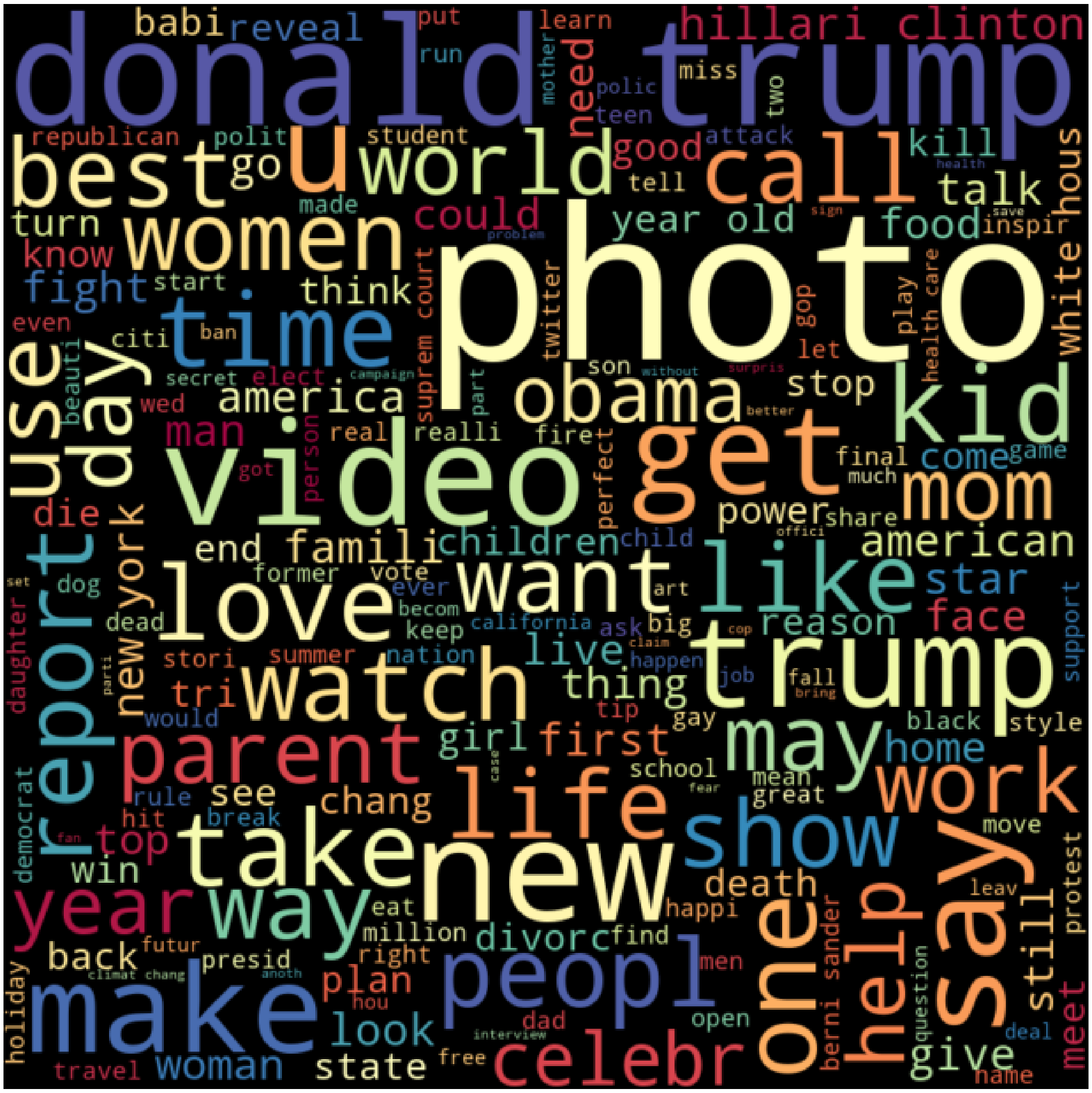
```
[39]: def process_column(df, column_name):
    # 1. Text Cleaning
    clean_text = df[column_name].apply(lambda x: preprocess_text(x))

    # 2. Tokenization - Tokenize the articles into words and punctuation.
    tokenized_text = clean_text.apply(word_tokenize)

    # 3. Removal of Stop Words
    stop_words = set(stopwords.words('english'))
    stop_words_removed = tokenized_text.apply(lambda x: [word for word in x if␣
↪word not in stop_words])

    # Bigrams and trigams reduced the classification accuracy so it has been␣
↪disabled.
    """
    # 4. Add Bi-grams
    # Convert the stop words removed tokenized data into a list of lists format␣
↪for bigram model training
    bigrams_input = stop_words_removed.tolist()
    # Create a bigram phraser. The bigram phrase must appear at least 5 times␣
↪to be considered.
    bigram = Phrases(bigrams_input, min_count=200, threshold=200)
    bigram_phraser = Phraser(bigram)
    # Apply the bigram phraser on the tokenized data
    bigram_output = [bigram_phraser[doc] for doc in bigrams_input]

    unique_bigrams = set()
    for doc in bigram_output[:2000]:
        for token in doc:
            if "_" in token:  # bigrams are represented with underscores
```

```
                unique_bigrams.add(token)

    print(f'Number of bigrams: {len(unique_bigrams)}')
    print(unique_bigrams)

    # Add Tri-grams - This is effectively the same process as bigrams, where a␣
↪third word may be added to a bigram word
    # if the sequence occurs sufficiently
    trigram = Phrases(bigram_output, min_count=5, threshold=30)
    trigram_phraser = Phraser(trigram)
    trigram_output = [trigram_phraser[bigram_phraser[doc]] for doc in␣
↪bigrams_input]
    """
    # Stemming
    stemmer = PorterStemmer()
    stemmed_words = stop_words_removed.apply(lambda x: [stemmer.stem(word) for␣
↪word in x])

    # Stemming was more accurate than lemmatization for the best model␣
↪performance.
    # 4. Perform lemmatization on all words.
    #lemmatizer = WordNetLemmatizer()
    #lemmatized_words = list(map(lambda doc: [lemmatizer.lemmatize(word) for␣
↪word in doc], stop_words_removed))

    # Convert lemmatized/stemmed words back to string format and add to the␣
↪dataframe
    processed_column_name = 'processed_' + column_name
    df[processed_column_name] = [' '.join(words) for words in stemmed_words]

    return df, stemmed_words
```

[40]:
```
# Select the Headline column to process
df, lemmatized_words = process_column(df, 'headline')
```

[41]:
```
# Plot a word cloud for the Headlines
plot_word_cloud(lemmatized_words, 'Headlines')
```

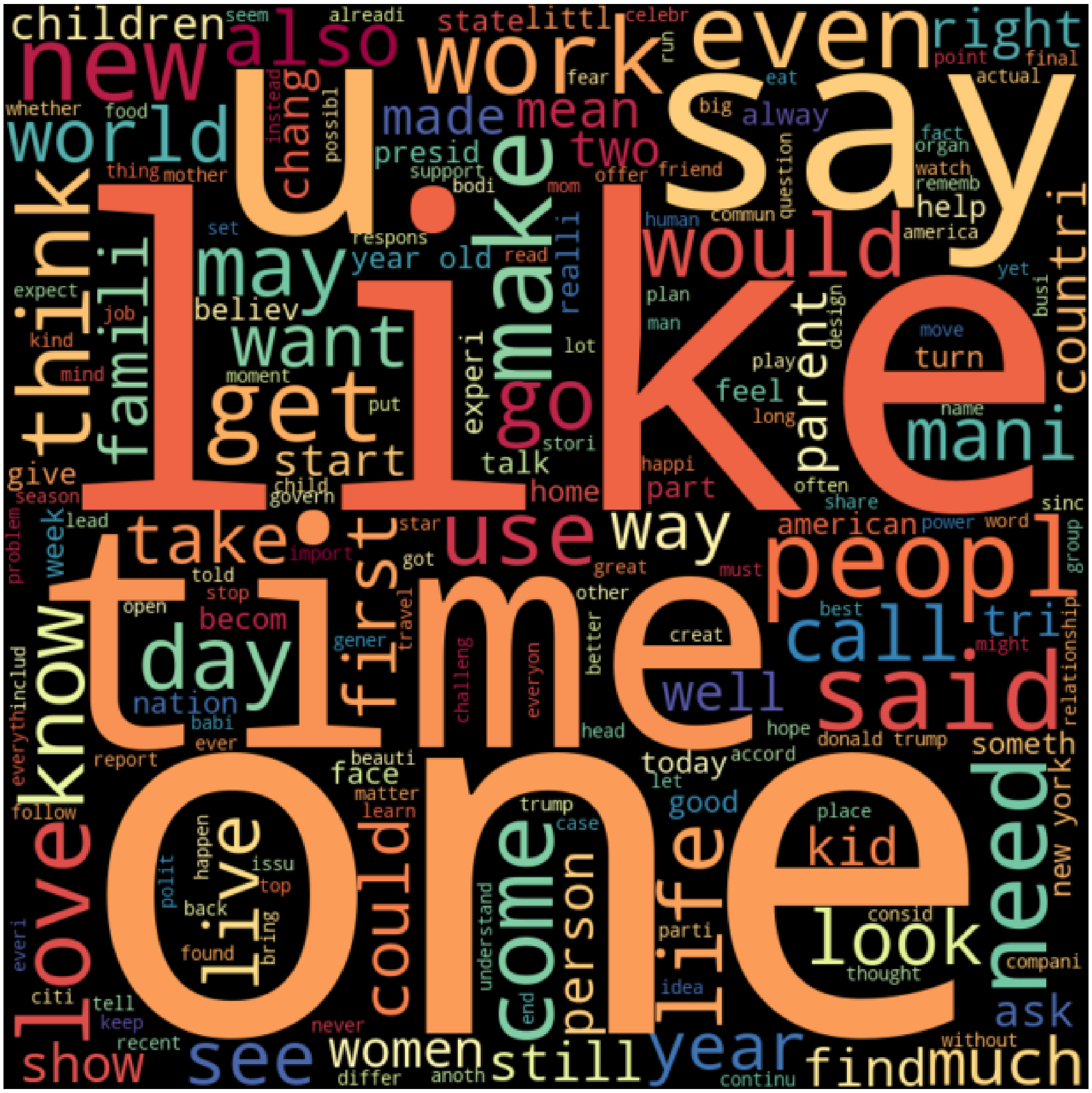
Word Cloud for Headlines



[42]:
```python
# Process the 'short description' column and plot the word cloud
df, lemmatized_words = process_column(df, 'short_description')
```

[43]:
```python
plot_word_cloud(lemmatized_words, 'short_description')
```

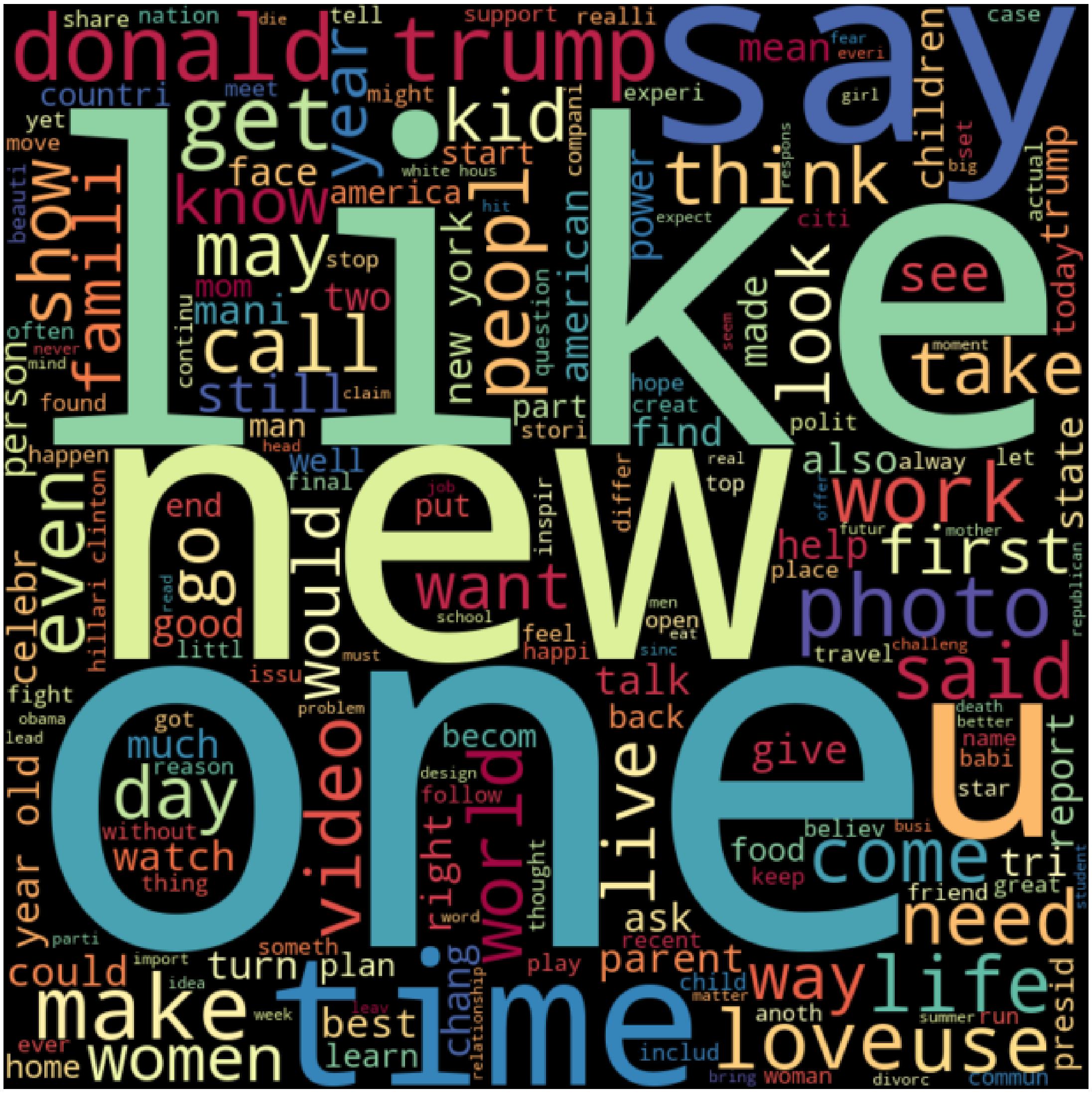
Word Cloud for short_description




```
[44]: # Process the 'combined info' column and plot the word cloud
      df, lemmatized_words = process_column(df, 'combined_info')
```

```
[45]: plot_word_cloud(lemmatized_words, 'combined_info')
```

Word Cloud for combined_info




```
[46]: df['combined_info'][100]
```

[46]: 'U.S.: Russia To Buy Rockets, Artillery Shells From North Korea The finding comes after the Biden administration confirmed that the Russian military in August took delivery of Iranian-manufactured drones for use in Ukraine.'

```
[47]: df['processed_combined_info'][100]
```

[47]: 'u russia buy rocket artilleri shell north korea find come biden administr confirm russian militari august took deliveri iranian manufactur drone use ukrain'

Split the data into training and test sets

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

[48]:
```
                                                link  \
0  https://www.huffpost.com/entry/covid-boosters-…
1  https://www.huffpost.com/entry/american-airlin…
2  https://www.huffpost.com/entry/funniest-tweets…
3  https://www.huffpost.com/entry/funniest-parent…
4  https://www.huffpost.com/entry/amy-cooper-lose…

                                            headline   category  \
0  Over 4 Million Americans Roll Up Sleeves For O…  U.S. NEWS
1  American Airlines Flyer Charged, Banned For Li…  U.S. NEWS
2  23 Of The Funniest Tweets About Cats And Dogs …     COMEDY
3  The Funniest Tweets From Parents This Week (Se…  PARENTING
4  Woman Who Called Cops On Black Bird-Watcher Lo…  U.S. NEWS

                                   short_description               authors  \
0  Health experts said it is too early to predict…  Carla K. Johnson, AP
1  He was subdued by passengers and crew when he …        Mary Papenfuss
2  "Until you have a dog you don't understand wha…         Elyse Wanshel
3  "Accidentally put grown-up toothpaste on my to…      Caroline Bologna
4  Amy Cooper accused investment firm Franklin Te…        Nina Golgowski

        date  word_count_headline  word_count_description  \
0 2022-09-23                   11                      29
1 2022-09-23                   13                      28
2 2022-09-23                   13                      12
3 2022-09-23                    9                      25
4 2022-09-22                   11                      25

                                       combined_info  word_count_combined  \
0  Over 4 Million Americans Roll Up Sleeves For O…                   40
1  American Airlines Flyer Charged, Banned For Li…                   41
2  23 Of The Funniest Tweets About Cats And Dogs …                   25
3  The Funniest Tweets From Parents This Week (Se…                   34
4  Woman Who Called Cops On Black Bird-Watcher Lo…                   36

   year  month                                processed_headline  \
0  2022      9  4 million american roll sleev omicron target c…
1  2022      9  american airlin flyer charg ban life punch fli…
2  2022      9          23 funniest tweet cat dog week sept 17 23
3  2022      9              funniest tweet parent week sept 17 23
4  2022      9  woman call cop black bird watcher lose lawsuit…

                         processed_short_description  \
0  health expert said earli predict whether deman…
1  subdu passeng crew fled back aircraft confront…
```

```
2                          dog understand could eaten
3   accident put grown toothpast toddler toothbrus…
4   ami cooper accus invest firm franklin templeto…

                              processed_combined_info
0   4 million american roll sleev omicron target c…
1   american airlin flyer charg ban life punch fli…
2   23 funniest tweet cat dog week sept 17 23 dog …
3   funniest tweet parent week sept 17 23 accident…
4   woman call cop black bird watcher lose lawsuit…
```

Removal of the unique words from "processed_combined_info"
Unique words that appear only once in the entire corpus will not be very useful for classification of categories. These words will be removed.

[49]:
```python
def remove_unique_words(df, column):
    # Extract all the words from all the speeches in the 'Processed_Text' column
    split_words = df[column].str.split().tolist()
    # Flatten the list of lists and count the frequency of each word
    word_frequency = Counter(word for row in split_words for word in row)
    print(f'word count: {len(word_frequency)}')
    # Obtain a set of all the words appearing only once (unique words)
    unique_words = set()
    for word, count in word_frequency.items():
        if count == 1:
            unique_words.add(word)
    print(f'num unique words: {len(unique_words)}')

    # Remove the unique words from all articles of the specified column
    col_without_unique = []
    for row in split_words:
        row_without_unique = []
        # Search through all words in each row and only keep the words that are
 ↪not in the unique word set
        for word in row:
            if word not in unique_words:
                row_without_unique.append(word)
        # Join the word lists into a string and append to the column series.
        col_without_unique.append(" ".join(row_without_unique))

    # Apply the column series to the specified column
    df[column] = col_without_unique
    return df
```

[50]:
```python
df = remove_unique_words(df, 'processed_combined_info')
```

```
word count: 62896
num unique words: 25711
```

There are 62,896 different words in the entire corpus. 25,711 words appear only once. They were removed from the corpus.

Split the data into training and test sets

[51]:
```
# 1. Split the data into training and test sets.
X_train, X_test, y_train, y_test =␣
↪train_test_split(df["processed_combined_info"],df["category"],test_size=0.2,
                                        stratify=df["category"], random_state=12,␣
↪shuffle=True)
```

2.1.2 Text Vectorization

Machine learning models require numerical input rather than textual, so text needs to be converted into vectors. Converting text into numerical data is called 'vectorization' or 'embedding'.

Bag of words is a basic method that converts text to vectors. Each word in the corpus is given an index and the word's frequency is associated with it. There are no more complex structures for this method.

It was observed that bag of words did not perform as well as tf-idf for the baseline. It will be evaluated again on the more complex models.

Term Frequency-Inverse Document Frequencies (Tf-Idf)
is a more advanced method. Instead of just counting the number of words, tf-Idf also adjusts word values based on their occurrence frequency in all the headline rows, reducing the weight to the more commonly occurring terms.

[52]:
```
# 2. Vectorization - Method 1 - This limits the number of features to the top␣
↪max_features most frequent terms
vectorizer = TfidfVectorizer(max_features=50000)
X_train_vec = vectorizer.fit_transform(X_train)
X_test_vec = vectorizer.transform(X_test)
```

[53]:
```
# The model was the highest accuracy deployed the previous method of Tf-idf␣
↪vectorization
"""
# 2. Vectorization - Method 2
# Exclude the words that appear in more than 95% of the combined_info entries␣
↪and
# Include only words that appear in 2 or more documents.

# Set up the TfidfVectorizer
tfidf_vectorizer = TfidfVectorizer(max_df=0.95, min_df=2, stop_words='english')

# Fit and transform the training data
X_train_vec = tfidf_vectorizer.fit_transform(X_train)

# Transform the test data
X_test_vec = tfidf_vectorizer.transform(X_test)
```

```
"""
```

[53]:
```
"\n# 2. Vectorization - Method 2\n# Exclude the words that appear in more than 95% of the combined_info entries and\n# Include only words that appear in 2 or more documents.\n\n# Set up the TfidfVectorizer\ntfidf_vectorizer = TfidfVectorizer(max_df=0.95, min_df=2, stop_words='english')\n\n# Fit and transform the training data\nX_train_vec = tfidf_vectorizer.fit_transform(X_train)\n\n# Transform the test data\nX_test_vec = tfidf_vectorizer.transform(X_test)\n"
```

This method was observed to work best for all the text vectorization methods tested, unless a high value of max_features was used in Method 1.

Word2vec

This is a more advanced neural network-based algorithm that learns word associations from a large corpus of text. Word2vec creates vectors of the words that are distributed numerical representations of word features – these word features could comprise of words that represent the context of the individual words present in our vocabulary. Word embeddings eventually help in establishing the association of a word with another similar meaning word through the created vectors. Credit: Analytics Vidhya.

It was observed that Word2vec did not perform as well as tf-idf for the baseline models. It will be evaluated again on the more complex models.

2.2 Machine Learning

Two models have been used as a baseline for testing the dataset. A Multinomial Naive-Bayes model and a Logistic Regression model. These are two basic models. The purpose of this section for the mid-semester report is to demonstrate that a baseline model can be used to produce an output on the chosen dataset. The models have been left with their default hyperparameter settings and were not tuned. For the final report, more advanced models will be evaluated and tuned to obtain maximum performance.

In the baseline, various text processing and vectorization steps were configured to determine which steps work best for this dataset. Please refer to the midsemester report for the evaluation of the pre-processing steps. The configuration shown here is for the best combination of all the preprocessing steps that were evaluated.

Note that the best result was achieved on the logistic regression model.

Multinomial Naive-Bayes Model

[54]:
```
# 3. Train the Naive-Bayes model
nb1 = MultinomialNB()
nb1.fit(X_train_vec, y_train)
```

[54]:
```
MultinomialNB()
```

[55]:
```
# 4. Evaluate the model
y_pred_nb1 = nb1.predict(X_test_vec)
```

[56]:
```python
# Display the model's classification accuracy
accuracy_nb1 = accuracy_score(y_test, y_pred_nb1)
print(f"Accuracy: {accuracy_nb1 * 100:.2f}%")

# Classification Report
sorted_labels = sorted(y_test.unique())
print("\nClassification Report:\n")
print(classification_report(y_test, y_pred_nb1, labels=sorted_labels))
```

```
Accuracy: 43.64%

Classification Report:


C:\Users\alang\anaconda3\envs\python310\lib\site-
packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

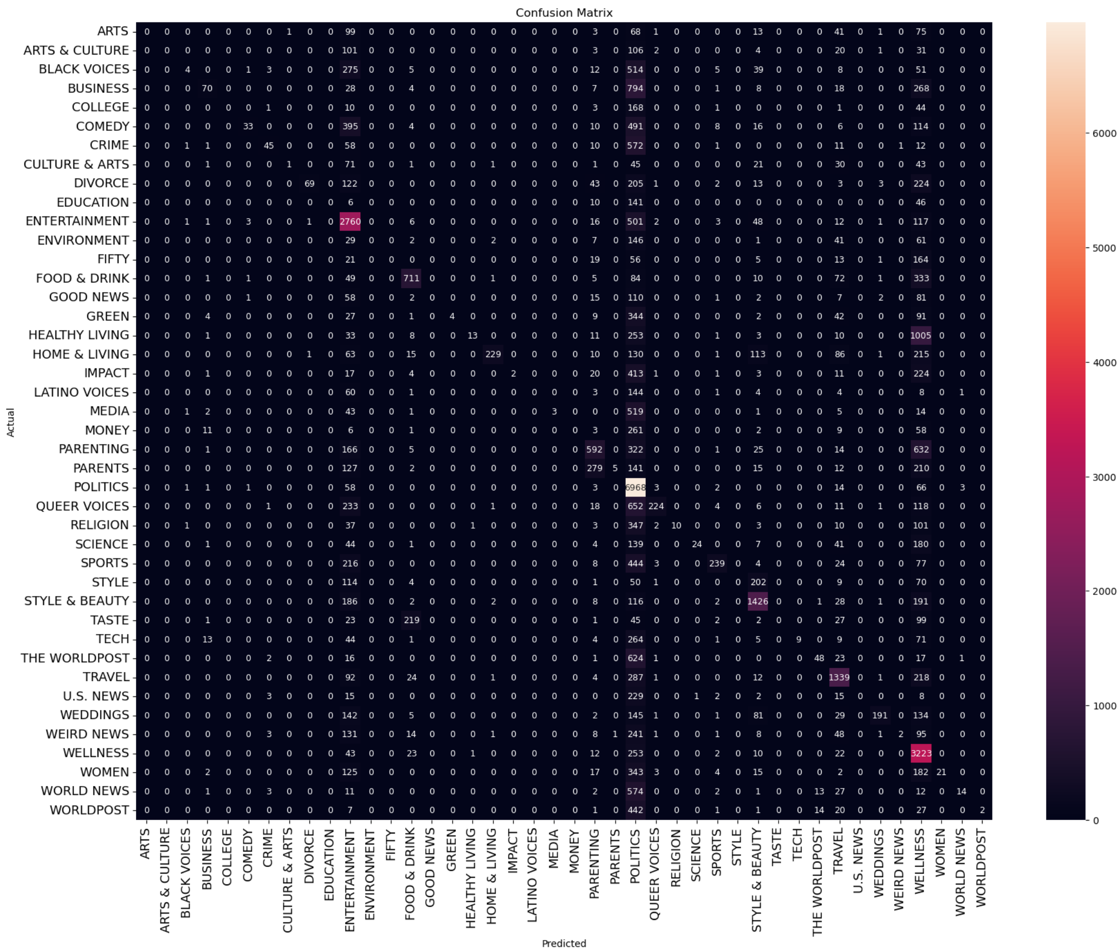
	precision	recall	f1-score	support
ARTS	0.00	0.00	0.00	302
ARTS & CULTURE	0.00	0.00	0.00	268
BLACK VOICES	0.44	0.00	0.01	917
BUSINESS	0.62	0.06	0.11	1198
COLLEGE	0.00	0.00	0.00	228
COMEDY	0.82	0.03	0.06	1077
CRIME	0.74	0.06	0.12	712
CULTURE & ARTS	0.50	0.00	0.01	215
DIVORCE	0.97	0.10	0.18	685
EDUCATION	0.00	0.00	0.00	203
ENTERTAINMENT	0.45	0.79	0.57	3472
ENVIRONMENT	0.00	0.00	0.00	289
FIFTY	0.00	0.00	0.00	279
FOOD & DRINK	0.67	0.56	0.61	1268
GOOD NEWS	0.00	0.00	0.00	279
GREEN	1.00	0.01	0.02	524
HEALTHY LIVING	0.87	0.01	0.02	1338
HOME & LIVING	0.96	0.27	0.42	864
IMPACT	1.00	0.00	0.01	697
LATINO VOICES	0.00	0.00	0.00	226
MEDIA	1.00	0.01	0.01	589
MONEY	0.00	0.00	0.00	351
PARENTING	0.50	0.34	0.40	1758
PARENTS	0.83	0.01	0.01	791
POLITICS	0.37	0.98	0.54	7120
QUEER VOICES	0.91	0.18	0.30	1269
RELIGION	1.00	0.02	0.04	515

```
       SCIENCE       0.96      0.05      0.10       441
        SPORTS       0.82      0.24      0.37      1015
         STYLE       0.00      0.00      0.00       451
STYLE & BEAUTY       0.67      0.73      0.70      1963
         TASTE       0.00      0.00      0.00       419
          TECH       1.00      0.02      0.04       421
 THE WORLDPOST       0.63      0.07      0.12       733
        TRAVEL       0.62      0.68      0.64      1979
     U.S. NEWS       0.00      0.00      0.00       275
      WEDDINGS       0.93      0.26      0.41       731
    WEIRD NEWS       0.67      0.00      0.01       555
      WELLNESS       0.36      0.90      0.51      3589
         WOMEN       1.00      0.03      0.06       714
    WORLD NEWS       0.74      0.02      0.04       660
     WORLDPOST       1.00      0.00      0.01       515

      accuracy                           0.44     41895
     macro avg       0.55      0.15      0.15     41895
  weighted avg       0.58      0.44      0.33     41895

C:\Users\alang\anaconda3\envs\python310\lib\site-
packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\alang\anaconda3\envs\python310\lib\site-
packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

For the Naive-Bayes model, the minority classes were often never predicted. Class imbalance is clearly an issue with this model.

[57]:
```python
# Generate the confusion matrix
conf_matrix_nb1 = confusion_matrix(y_test, y_pred_nb1, labels=sorted_labels)

# Plot the confusion matrix
plt.figure(figsize=(20, 15))
sns.heatmap(conf_matrix_nb1, annot=True, fmt="d", annot_kws={"size": 9},
            xticklabels=sorted_labels, yticklabels=sorted_labels, cmap="rocket")

# Set the plot configurations
plt.xticks(fontsize=13)
plt.yticks(fontsize=13)
plt.ylabel('Actual')
plt.xlabel('Predicted')
```

```python
plt.title('Confusion Matrix')
plt.show()
```



Logistic Regression Model

[58]:
```python
# 3. Train the Logistic Regression model
lr1 = LogisticRegression(max_iter=600, random_state=12)
lr1.fit(X_train_vec, y_train)
```

[58]: LogisticRegression(max_iter=600, random_state=12)

[59]:
```python
# 4. Evaluate the model
y_pred_lr1 = lr1.predict(X_test_vec)
```

[60]:
```python
# Verify the predictions and test set label counts.
from collections import Counter

label_counts = Counter(y_pred_lr1)
```

```python
print(label_counts)
```

```
Counter({'POLITICS': 9189, 'WELLNESS': 5413, 'ENTERTAINMENT': 4891, 'TRAVEL':
2380, 'STYLE & BEAUTY': 2243, 'PARENTING': 2171, 'FOOD & DRINK': 1524,
'BUSINESS': 1120, 'QUEER VOICES': 1056, 'SPORTS': 996, 'HOME & LIVING': 832,
'COMEDY': 754, 'WEDDINGS': 719, 'CRIME': 694, 'HEALTHY LIVING': 666, 'BLACK
VOICES': 591, 'DIVORCE': 587, 'THE WORLDPOST': 552, 'WOMEN': 492, 'GREEN': 459,
'IMPACT': 429, 'WORLD NEWS': 397, 'MEDIA': 383, 'RELIGION': 373, 'PARENTS': 358,
'WEIRD NEWS': 334, 'SCIENCE': 304, 'TECH': 280, 'WORLDPOST': 265, 'MONEY': 235,
'ARTS': 168, 'COLLEGE': 156, 'STYLE': 145, 'EDUCATION': 126, 'ENVIRONMENT': 101,
'ARTS & CULTURE': 96, 'TASTE': 86, 'GOOD NEWS': 81, 'FIFTY': 77, 'CULTURE &
ARTS': 73, 'LATINO VOICES': 64, 'U.S. NEWS': 35})
```

[61]:
```python
label_counts2 = Counter(y_test)
print(label_counts2)
```

```
Counter({'POLITICS': 7120, 'WELLNESS': 3589, 'ENTERTAINMENT': 3472, 'TRAVEL':
1979, 'STYLE & BEAUTY': 1963, 'PARENTING': 1758, 'HEALTHY LIVING': 1338, 'QUEER
VOICES': 1269, 'FOOD & DRINK': 1268, 'BUSINESS': 1198, 'COMEDY': 1077, 'SPORTS':
1015, 'BLACK VOICES': 917, 'HOME & LIVING': 864, 'PARENTS': 791, 'THE
WORLDPOST': 733, 'WEDDINGS': 731, 'WOMEN': 714, 'CRIME': 712, 'IMPACT': 697,
'DIVORCE': 685, 'WORLD NEWS': 660, 'MEDIA': 589, 'WEIRD NEWS': 555, 'GREEN':
524, 'WORLDPOST': 515, 'RELIGION': 515, 'STYLE': 451, 'SCIENCE': 441, 'TECH':
421, 'TASTE': 419, 'MONEY': 351, 'ARTS': 302, 'ENVIRONMENT': 289, 'GOOD NEWS':
279, 'FIFTY': 279, 'U.S. NEWS': 275, 'ARTS & CULTURE': 268, 'COLLEGE': 228,
'LATINO VOICES': 226, 'CULTURE & ARTS': 215, 'EDUCATION': 203})
```

[62]:
```python
# Display the model's classififcation accuracy
accuracy = accuracy_score(y_test, y_pred_lr1)
print(f"Accuracy: {accuracy * 100:.2f}%")

# Displaying the classification report
sorted_labels = sorted(y_test.unique())
print("\nClassification Report:\n")
print(classification_report(y_test, y_pred_lr1, labels=sorted_labels))
```

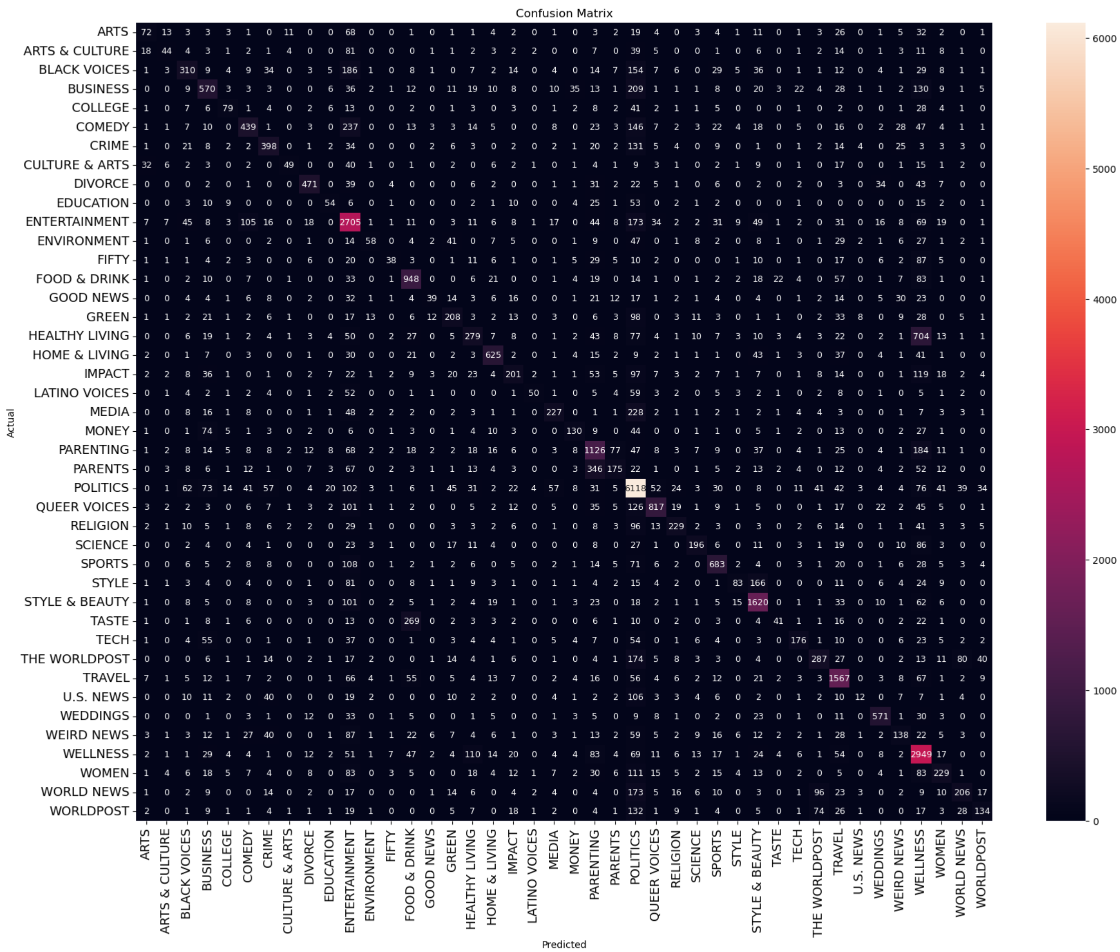
```
Accuracy: 60.51%

Classification Report:

                precision    recall  f1-score   support

          ARTS       0.43      0.24      0.31       302
ARTS & CULTURE       0.46      0.16      0.24       268
  BLACK VOICES       0.52      0.34      0.41       917
      BUSINESS       0.51      0.48      0.49      1198
       COLLEGE       0.51      0.35      0.41       228
        COMEDY       0.58      0.41      0.48      1077
         CRIME       0.57      0.56      0.57       712
```

```
 CULTURE & ARTS       0.67      0.23      0.34       215
        DIVORCE       0.80      0.69      0.74       685
      EDUCATION       0.43      0.27      0.33       203
  ENTERTAINMENT       0.55      0.78      0.65      3472
    ENVIRONMENT       0.57      0.20      0.30       289
          FIFTY       0.49      0.14      0.21       279
   FOOD & DRINK       0.62      0.75      0.68      1268
      GOOD NEWS       0.48      0.14      0.22       279
          GREEN       0.45      0.40      0.42       524
 HEALTHY LIVING       0.42      0.21      0.28      1338
  HOME & LIVING       0.75      0.72      0.74       864
         IMPACT       0.47      0.29      0.36       697
  LATINO VOICES       0.78      0.22      0.34       226
          MEDIA       0.59      0.39      0.47       589
          MONEY       0.55      0.37      0.44       351
      PARENTING       0.52      0.64      0.57      1758
        PARENTS       0.49      0.22      0.30       791
       POLITICS       0.67      0.86      0.75      7120
   QUEER VOICES       0.77      0.64      0.70      1269
       RELIGION       0.61      0.44      0.52       515
        SCIENCE       0.64      0.44      0.53       441
         SPORTS       0.69      0.67      0.68      1015
          STYLE       0.57      0.18      0.28       451
 STYLE & BEAUTY       0.72      0.83      0.77      1963
          TASTE       0.48      0.10      0.16       419
           TECH       0.63      0.42      0.50       421
  THE WORLDPOST       0.52      0.39      0.45       733
         TRAVEL       0.66      0.79      0.72      1979
      U.S. NEWS       0.34      0.04      0.08       275
       WEDDINGS       0.79      0.78      0.79       731
     WEIRD NEWS       0.41      0.25      0.31       555
       WELLNESS       0.54      0.82      0.66      3589
          WOMEN       0.47      0.32      0.38       714
     WORLD NEWS       0.52      0.31      0.39       660
      WORLDPOST       0.51      0.26      0.34       515

       accuracy                           0.61     41895
      macro avg       0.57      0.42      0.46     41895
   weighted avg       0.59      0.61      0.58     41895
```

[63]:

```python
# Generate the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_lr1, labels=sorted_labels)

# Plot the confusion matrix
plt.figure(figsize=(20, 15))
sns.heatmap(conf_matrix, annot=True, fmt="d", annot_kws={"size": 9},
```

```
             xticklabels=sorted_labels, yticklabels=sorted_labels, cmap="rocket")

# Set the plot configurations
plt.xticks(fontsize=13)
plt.yticks(fontsize=13)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Confusion Matrix')
plt.show()
```



The best model is the logistic regression model which not only had a much higher accuracy than the Naive-Bayes, but it also made predictions for every label. Further work will continue on this project with more advanced classifiers.

[ ]:

```

```