AIT Undersampling Evaluation

October 26, 2023

1 AIT Project - Final Project Undersampling

Alan Gaugler
U885853
October 26, 2023

In the final project, I investigated if undersampling would be beneficial in addressing class imbalance. The results degraded the overall accuracy, so it was not included in the final project notebook. The work however is attached here for reference. Refer to the final project notebook for details of the final work that was carried out.

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

[3]:
```
# Set Pandas option to display the entire content in a column
pd.set_option('display.max_colwidth', None)
```

[4]:
```
# Display the header
df.head()
```

[4]:
```
                                                                   link  \
0
https://www.huffpost.com/entry/covid-boosters-uptake-
us_n_632d719ee4b087fae6feaac9
1  https://www.huffpost.com/entry/american-airlines-passenger-banned-flight-
attendant-punch-justice-department_n_632e25d3e4b0e247890329fe
2                                      https://www.huffpost.com/entry/funniest-
tweets-cats-dogs-september-17-23_n_632de332e4b0695c1d81dc02
3
https://www.huffpost.com/entry/funniest-parenting-
tweets_l_632d7d15e4b0d12b5403e479
4                     https://www.huffpost.com/entry/amy-cooper-loses-
discrimination-lawsuit-franklin-templeton_n_632c6463e4b09d8701bd227e

    headline  \
0                Over 4 Million Americans Roll Up Sleeves For Omicron-Targeted
COVID Boosters
1  American Airlines Flyer Charged, Banned For Life After Punching Flight
Attendant On Video
2                       23 Of The Funniest Tweets About Cats And Dogs This Week
(Sept. 17-23)
3                                    The Funniest Tweets From Parents This Week
(Sept. 17-23)
4               Woman Who Called Cops On Black Bird-Watcher Loses Lawsuit Against
Ex-Employer

    category  \
0  U.S. NEWS
1  U.S. NEWS
2     COMEDY
3  PARENTING
4  U.S. NEWS
```

```
short_description  \
0       Health experts said it is too early to predict whether demand would
match up with the 171 million doses of the new boosters the U.S. ordered for the
fall.
1  He was subdued by passengers and crew when he fled to the back of the
aircraft after the confrontation, according to the U.S. attorney's office in Los
Angeles.
2
"Until you have a dog you don't understand what could be eaten."
3  "Accidentally put grown-up toothpaste on my toddler’s toothbrush and he
screamed like I was cleaning his teeth with a Carolina Reaper dipped in Tabasco
sauce."
4     Amy Cooper accused investment firm Franklin Templeton of unfairly firing
her and branding her a racist after video of the Central Park encounter went
viral.

                authors        date
0  Carla K. Johnson, AP 2022-09-23
1        Mary Papenfuss 2022-09-23
2         Elyse Wanshel 2022-09-23
3      Caroline Bologna 2022-09-23
4        Nina Golgowski 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 identifying the article category. **authors:** The names of the article's authors. **date:** The date of the article's publication.

[5]:
```
df.shape
```

[5]:
```
(209527, 6)
```

This is a large dataset with 209527 articles.

[6]:
```
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.

[7]:
```
df.describe()
```

```
C:\Users\alang\AppData\Local\Temp\ipykernel_17920\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()
```

[7]:
```
                           link  \
count
209527
unique
209486
top
https://www.huffingtonpost.comhttps://www.washingtonpost.com/politics/divisions-
within-gop-over-trumps-candidacy-are-
growing/2016/02/28/97b16010-de3a-11e5-8d98-4b3d9215ade1_story.html
freq
2
first
NaN
last
NaN

              headline  category short_description authors  \
count           209527    209527            209527  209527
unique          207996        42            187022   29169
top     Sunday Roundup  POLITICS
freq                90     35602             19712   37418
first              NaN       NaN               NaN     NaN
last               NaN       NaN               NaN     NaN

                       date
count                209527
unique                 3890
top     2014-03-25 00:00:00
freq                    100
first   2012-01-28 00:00:00
last    2022-09-23 00:00:00
```

[8]:
```
# Find the number of missing values in each column
df.isna().sum()
```

[8]:
```
link                 0
headline             0
category             0
short_description    0
authors              0
date                 0
dtype: int64
```

There are no missing values in the dataset.

[9]:
```
# Are there any duplicate headlines?
df['headline'].value_counts()
```

[9]:
```
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.

[10]:
```
# Are there any duplicate short descriptions?
df['short_description'].value_counts()
```

[10]:
```
                                                  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.

[11]:
```
# Display all the categories
df['category'].unique()
```

[11]:
```
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)
```

[12]:
```
df['category'].nunique()
```

[12]:
```
42
```

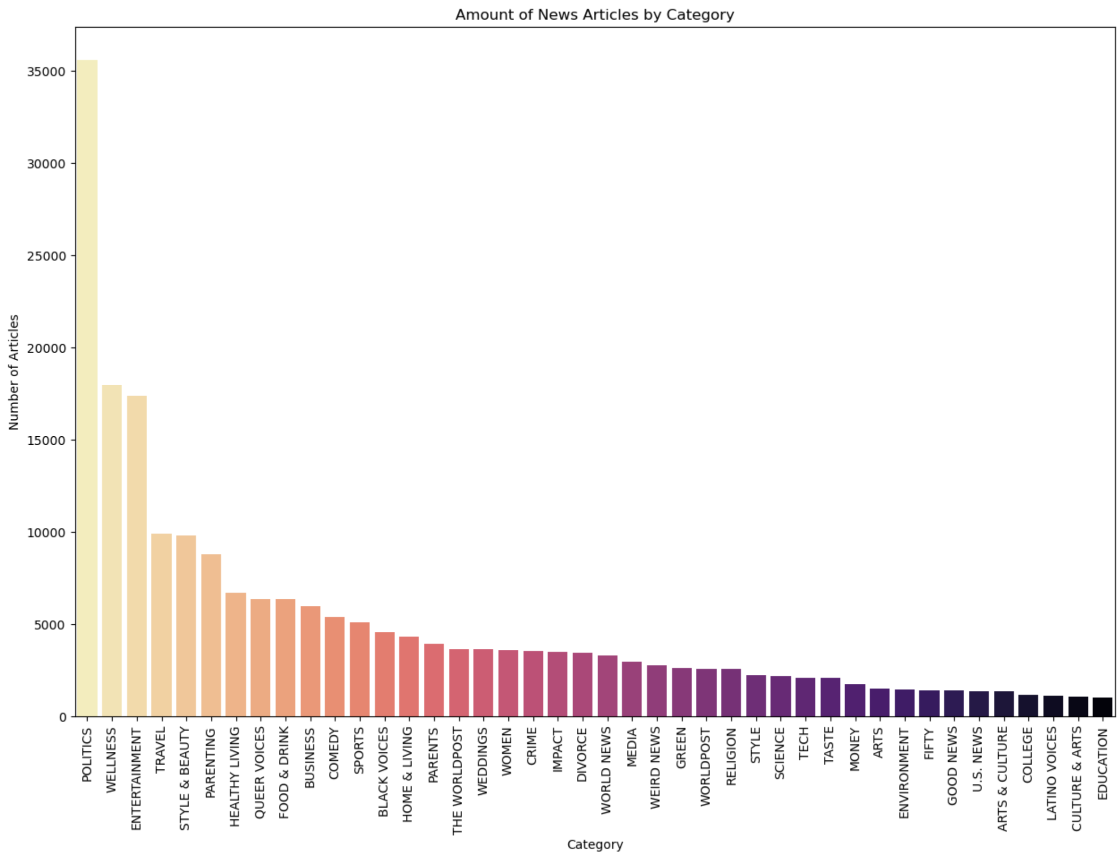
There are 42 unique values. These will be the categories.

[13]:
```
# Display the number of articles per category
df['category'].value_counts()
```

[13]:
```
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
```

[14]:
```python
# 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()
```

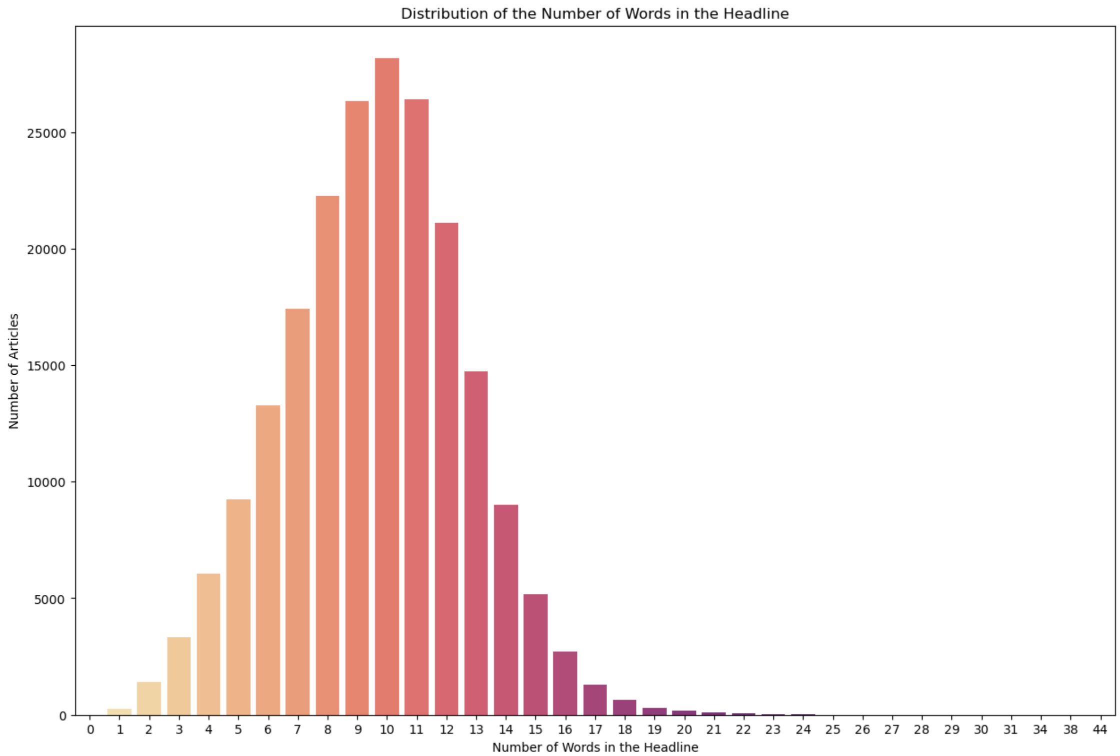


Politics is by far the most common category in this dataset, followed by wellness and entertainment. This dataset is clearly very imbalanced. This will produce challenges in predicting the minority categories.

[15]:
```
# 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()))
```

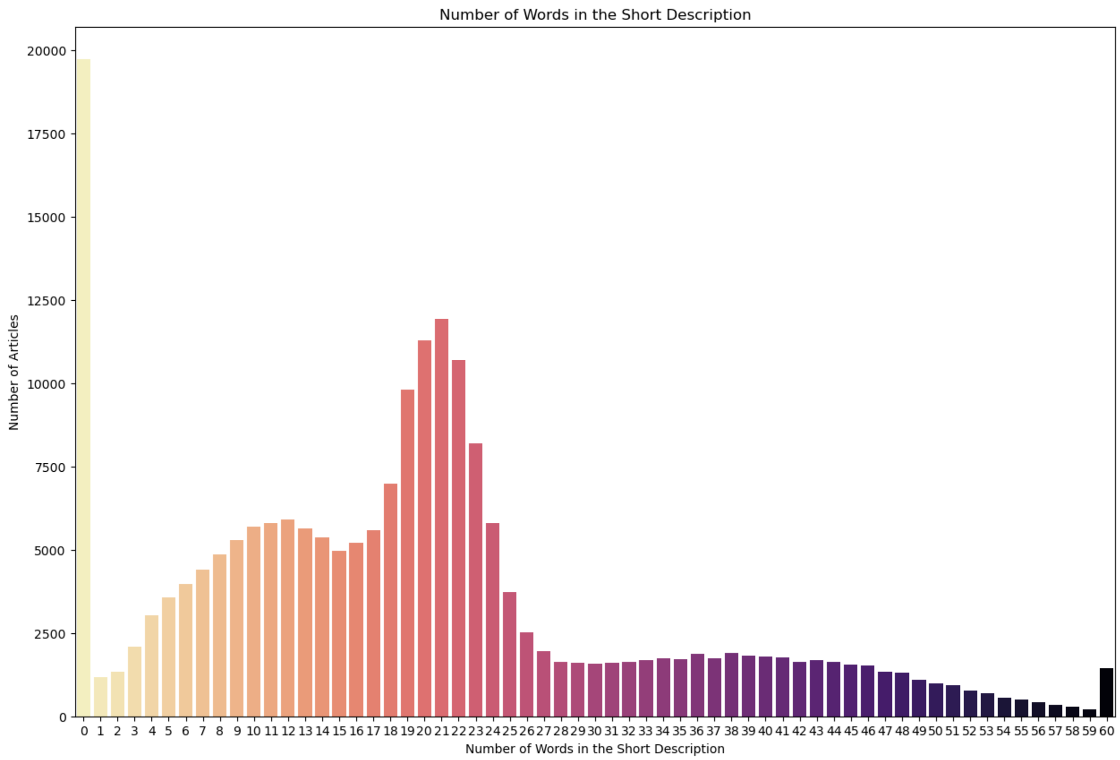
[16]:
```
# Plot the Distribution of the Number of Words in the Headline.
plt.figure(figsize=(15, 10))
ax = sns.countplot(x=df['word_count_headline'],
                   order=df['word_count_headline'].value_counts().
↪sort_index(ascending=True).index,
                   palette="magma_r")
plt.title('Distribution 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, centred on 10 words.

[17]:
```
# 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()
```



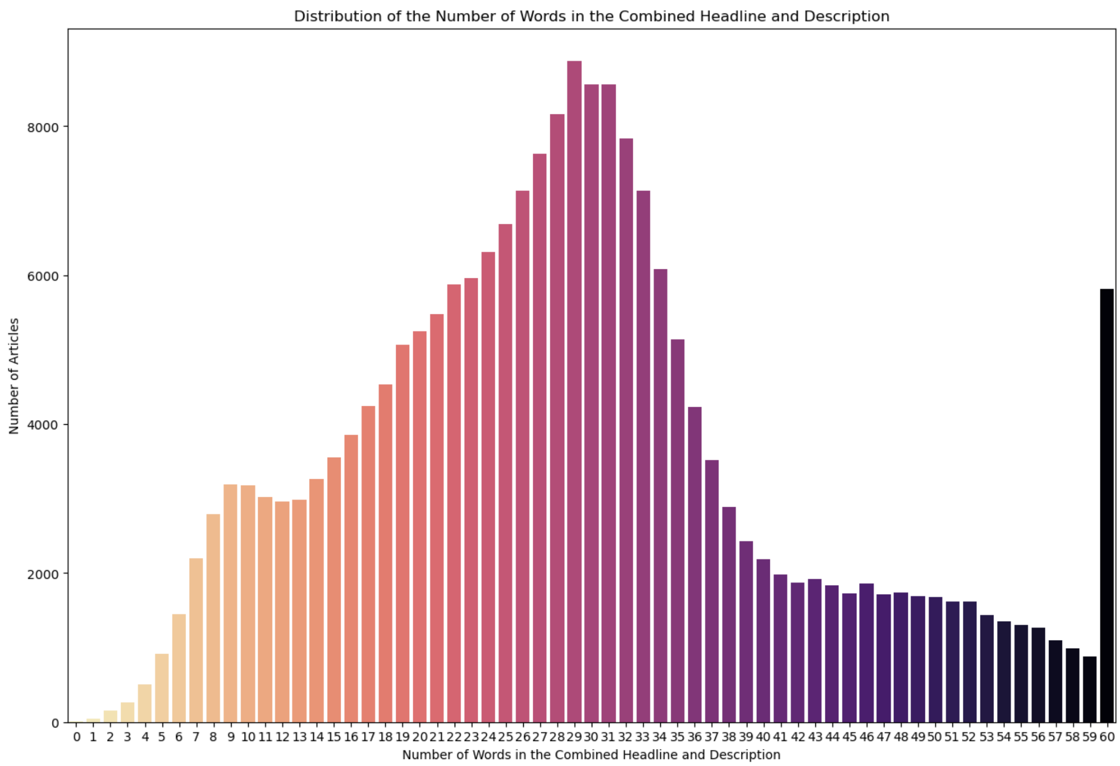
Looking at the plot above, there are 19712 articles in this dataset that do not have a description, but rather just a headline. The number 60 is actually 60+. This has been capped for this plot only but not for the actual dataset. The distribution of the number of words in the short description interestingly 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'.

[18]:
```
# 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()))
```

[19]:
```
# 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.

[20]:
```
# Are there any duplicates in the combined info column?
df['combined_info'].value_counts()
```

[20]:
```
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
```

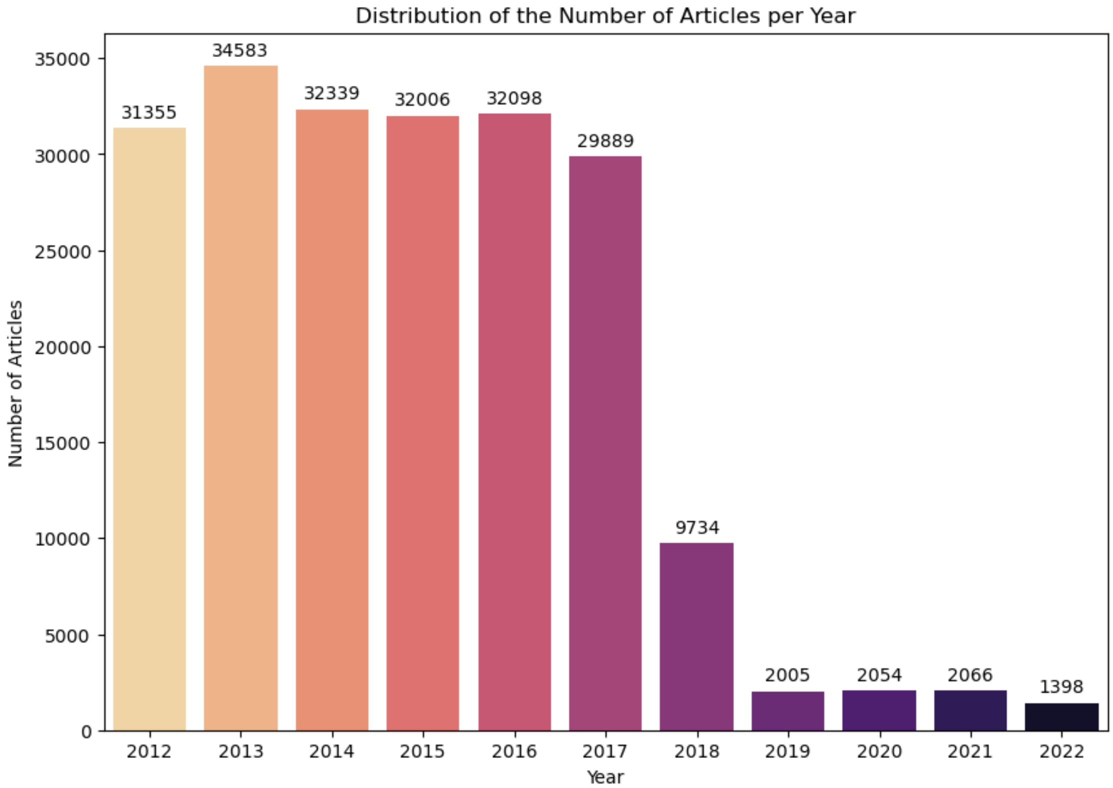
```
33
The 20 Funniest Tweets From Women This Week The ladies of Twitter never fail to
brighten our days with their brilliant   but succinct   wisdom. Each week,
HuffPost Women                                   30
Best Parenting Tweets: What Moms And Dads Said On Twitter This Week Kids may say
the darndest 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.

[21]:
```
# 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
```

[22]:
```
# 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
```

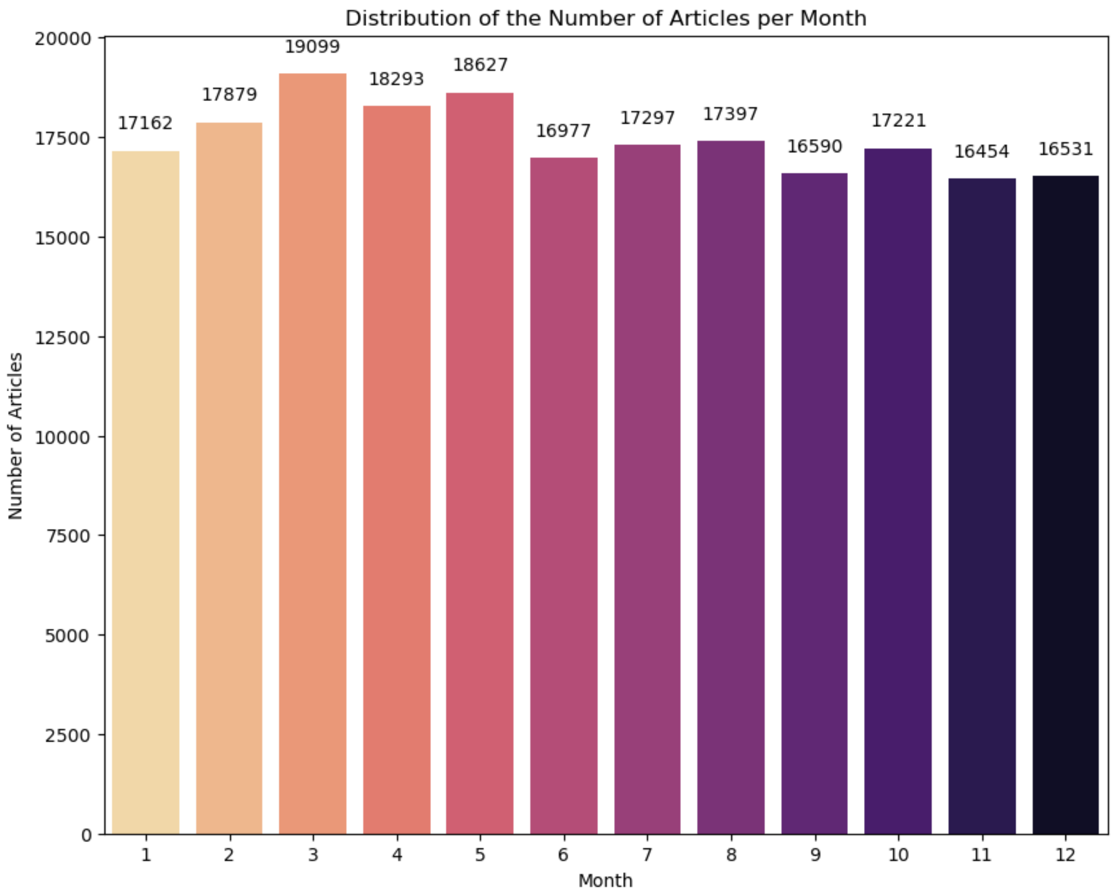
```
            height + 550,  # set the text slightly above the bar
            '{:1.0f}'.format(height),
            ha="center")

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.

[23]:
```
# 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.

[24]:
```
df.describe()
```

[24]:
```
       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
```

[25]:

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

[25]:

```
link  \
63714
https://www.huffingtonpost.com/entry/manscraping_b_10573084.html
66196                    https://www.huffingtonpost.com/entry/tire-
d_b_10193554.html
66203
https://www.huffingtonpost.com/entry/wafflewich_b_10197956.html
72366
https://www.huffingtonpost.com/entry/hangman_b_9506810.html
78481
https://www.huffingtonpost.com/entry/hugs_b_8950534.html
81477
https://www.huffingtonpost.com/entry/memories_b_8730174.html
81496  https://www.huffingtonpost.com/entry/what-to-do-about-
disloyal_b_8734900.html
82119
https://www.huffingtonpost.com/entry/podcast_b_8674486.html
86508               https://www.huffingtonpost.com/entry/the-
idealist_b_8277718.html
90944
https://www.huffingtonpost.com/entry/lincoln-20_b_8023742.html

            headline  category short_description  \
63714  "ManScraping"    COMEDY
66196         Tire-d    COMEDY
66203     Wafflewich     TASTE
72366        Hangman    COMEDY
78481           Hugs    COMEDY
81477       Memories    COMEDY
81496        IGNORE.  POLITICS
```

```
82119        Podcast    COMEDY
86508          Once.    COMEDY
90944                 POLITICS

          authors  \
63714                                                    Tom Kramer,
ContributorWriter of the Wry
66196                                          Marcia Liss, Contributor(Almost)
Famous Cartoonist
66203  Dough Mamma, ContributorPrivate chef, culinary school graduate and
second-generation f…
72366                                          Marcia Liss, Contributor(Almost)
Famous Cartoonist
78481                                          Marcia Liss, Contributor(Almost)
Famous Cartoonist
81477                                          Marcia Liss, Contributor(Almost)
Famous Cartoonist
81496                             Gabriela Rivera-Morales, ContributorBlog
Editor, Huffington Post
82119                                          Marcia Liss, Contributor(Almost)
Famous Cartoonist
86508                                          Marcia Liss, Contributor(Almost)
Famous Cartoonist
90944  Robert Moran, ContributorRobert Moran leads Brunswick Insight, and writes
and speaks on…

            date  word_count_headline  word_count_description   combined_info  \
63714 2016-06-26                    1                       0  "ManScraping"
66196 2016-05-29                    1                       0          Tire-d
66203 2016-05-29                    1                       0      Wafflewich
72366 2016-03-19                    1                       0         Hangman
78481 2016-01-10                    1                       0            Hugs
81477 2015-12-06                    1                       0        Memories
81496 2015-12-06                    1                       0         IGNORE.
82119 2015-11-29                    1                       0         Podcast
86508 2015-10-11                    1                       0           Once.
90944 2015-08-22                    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
```

[26]:
```
len(df[df['word_count_combined'] <= 1])
```

[26]:
```
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.

[27]:
```
df = df[df['word_count_combined'] > 1].copy()
```

[28]:
```
df.shape
```

[28]:
```
(209474, 12)
```

2.0.2 Reduce the Number of News Categories

It was observed that many of the article categories are very similar. This will now be investigated further with the aim of merging two or more topics that are similar.

[29]:
```
# Display all the categories
df['category'].unique()
```

[29]:
```
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)
```

Observing above, there are 42 categories. There are many examples of where two or more categories are very similar and could even be considered the same. To make the classification task more realistic, some of these categories can be merged together. After careful consideration, it is been decided to merge the following categories:

[30]:
```
# Make a new feature called 'category_red' (reduced)
df['category_red'] = df['category']
```

[31]:
```
# Relabel one category to another related category
df['category_red']=df['category_red'].replace({'PARENTS': 'PARENTING',
                                        'THE WORLDPOST': 'WORLD NEWS',
                                        'WORLDPOST': 'WORLD NEWS',
                                        'BUSINESS': 'BUSINESS & FINANCE',
                                        'MONEY': 'BUSINESS & FINANCE',
```

```
                                        'COLLEGE': 'EDUCATION',
                                        'STYLE': 'STYLE & BEAUTY',
                                        'GREEN': 'ENVIRONMENT',
                                        'ARTS': 'ARTS & CULTURE',
                                        'CULTURE & ARTS': 'ARTS & CULTURE',
                                        'HEALTHY LIVING': 'WELLNESS',
                                        'TASTE': 'FOOD & DRINK'})
```

It may have been possible to further reduce the number of articles, by combining the 'BLACK VOICES', 'QUEER VOICES' and 'LATINO VOICES' categories together and also maybe 'SCIENCE' and 'TECH' and possibly more, but I consider those to be too distinct from each other. The choices of categories I made above I believe are similar enough to be merged together.

[32]:
```
 #Left out for now



df['category']=df['category'].replace({
"QUEER VOICES": "GROUPS VOICES",

"BLACK VOICES": "GROUPS VOICES",



"SCIENCE": "SCIENCE & TECH",
"TECH": "SCIENCE & TECH",

"LATINO VOICES": "GROUPS VOICES",

"FIFTY": "MISCELLANEOUS",
"GOOD NEWS": "MISCELLANEOUS"})
```

[33]:
```
filtered_df = df[df['category'] == 'TASTE']
filtered_df.head()
```

[33]:
```
                     link  \
16173     https://www.huffingtonpost.com/entry/ice-water-restaurants-
american_us_5a5683bce4b08a1f624b0f17
16242         https://www.huffingtonpost.com/entry/pineapple-casserole-
recipe_us_5a562ef6e4b0d614e48b9b98
16516  https://www.huffingtonpost.com/entry/how-to-get-a-bartenders-
attention_us_5a55372ce4b0b117f88041e3
16599         https://www.huffingtonpost.com/entry/diet-coke-makeover-
twitter_us_5a5676a9e4b08a1f624afc32
16776            https://www.huffingtonpost.com/entry/sunions-tearless-
onions_us_5a4fa3c2e4b003133ec776d5

                                                                  headline  \
```

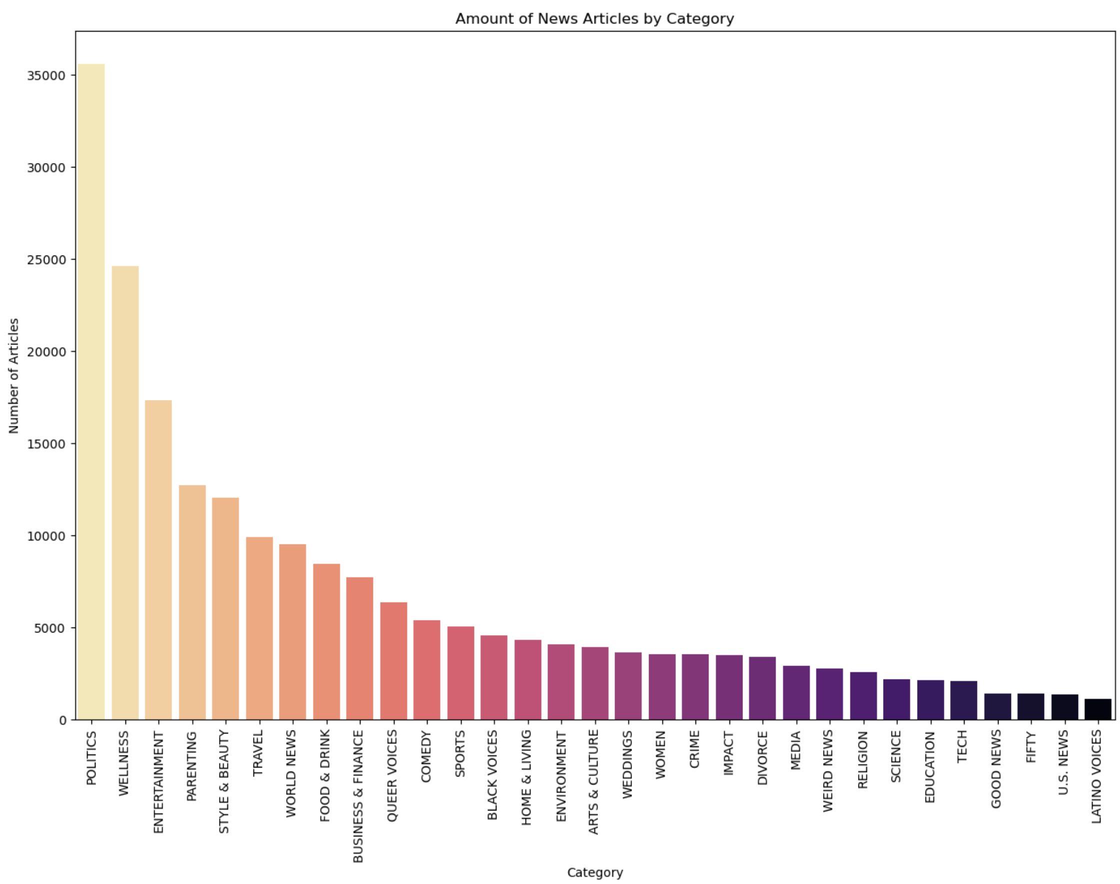
```
16173      It's Weird That American Restaurants Serve Ice Water In Winter
16242  Pineapple Casserole, The Southern Dish That's A Paradox Of Flavors
16516                            How To Actually Get A Bartender's Attention
16599    Diet Coke's Millennial-Inspired Makeover Leaves People Befuddled
16776      We Tested The New 'Tearless' Onions To See If They Really Work

      category                                    short_description  \
16173    TASTE  But why do we even have ice in our drinks in the first place?
16242    TASTE         It's got pineapple, cheddar and a whole lot of butter.
16516    TASTE                          Plus other things they wish you knew.
16599    TASTE                It's not like a regular soda, it's a cool soda.
16776    TASTE                                 Put away your goggles, people.

                authors       date  word_count_headline  \
16173   Todd Van Luling 2018-01-16                   10
16242     Kristen Aiken 2018-01-16                   10
16516    Taylor Pittman 2018-01-11                    7
16599  Abigail Williams 2018-01-10                    7
16776     Kristen Aiken 2018-01-08                   12

       word_count_description  \
16173                      14
16242                      10
16516                       7
16599                      10
16776                       5

                                          combined_info  \
16173  It's Weird That American Restaurants Serve Ice Water In Winter But why do
we even have ice in our drinks in the first place?
16242     Pineapple Casserole, The Southern Dish That's A Paradox Of Flavors
It's got pineapple, cheddar and a whole lot of butter.
16516                                                   How To Actually Get A
Bartender's Attention Plus other things they wish you knew.
16599              Diet Coke's Millennial-Inspired Makeover Leaves People
Befuddled It's not like a regular soda, it's a cool soda.
16776                                     We Tested The New 'Tearless' Onions To See
If They Really Work Put away your goggles, people.

       word_count_combined  year  month  category_red
16173                   24  2018      1  FOOD & DRINK
16242                   20  2018      1  FOOD & DRINK
16516                   14  2018      1  FOOD & DRINK
16599                   17  2018      1  FOOD & DRINK
16776                   17  2018      1  FOOD & DRINK
```

[34]:
```
# Display the number of reduced categories
df['category_red'].nunique()
```

[34]: 31

The number of categories has now been reduced from 42 to 31. This is a reduction of 11 categories.

[35]:
```
# Plot the distribution of news articles by news category.
plt.figure(figsize=(15, 10))
ax = sns.countplot(x=df['category_red'], order=df['category_red'].
 ↪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()
```



There is still a large imbalance between the majority and the minority classes, which will still be a challenge. This will be investigated.

Display the number of articles per category

[36]:
```
# Display the number of articles per category
category_counts = df['category_red'].value_counts()
category_counts
```

[36]:
```
POLITICS              35598
WELLNESS              24633
ENTERTAINMENT         17360
PARENTING             12746
STYLE & BEAUTY        12068
TRAVEL                 9897
WORLD NEWS             9540
FOOD & DRINK           8435
BUSINESS & FINANCE     7745
QUEER VOICES           6346
COMEDY                 5384
SPORTS                 5075
BLACK VOICES           4583
HOME & LIVING          4320
ENVIRONMENT            4066
ARTS & CULTURE         3922
WEDDINGS               3653
WOMEN                  3570
CRIME                  3562
IMPACT                 3483
DIVORCE                3426
MEDIA                  2943
WEIRD NEWS             2776
RELIGION               2576
SCIENCE                2206
EDUCATION              2157
TECH                   2104
GOOD NEWS              1397
FIFTY                  1396
U.S. NEWS              1377
LATINO VOICES          1130
Name: category_red, dtype: int64
```

2.0.3 Undersampling of Majority Classes

To reduce training time for this large dataset and to address the large class imbalance among the 31 classes, undersampling will be performed. I will reduce the dataset to approximately 50,000 news article samples, which is approximately 24% of the original dataset size. This means that the maximum number of samples per class is 1656.

[37]:
```
# Import the required library
from sklearn.utils import resample
```

[38]:
```
# Define a threshold for the maximum number of articles per category.
max_articles_per_category = 1656
```

[39]:
```
# Obtain a list of categories that will be reduced
categories_to_reduce = category_counts[category_counts >␣
↪max_articles_per_category].index
```

[40]:
```
categories_to_reduce
```

[40]:
```
Index(['POLITICS', 'WELLNESS', 'ENTERTAINMENT', 'PARENTING', 'STYLE & BEAUTY',
       'TRAVEL', 'WORLD NEWS', 'FOOD & DRINK', 'BUSINESS & FINANCE',
       'QUEER VOICES', 'COMEDY', 'SPORTS', 'BLACK VOICES', 'HOME & LIVING',
       'ENVIRONMENT', 'ARTS & CULTURE', 'WEDDINGS', 'WOMEN', 'CRIME', 'IMPACT',
       'DIVORCE', 'MEDIA', 'WEIRD NEWS', 'RELIGION', 'SCIENCE', 'EDUCATION',
       'TECH'],
      dtype='object')
```

[41]:
```
len(categories_to_reduce)
```

[41]:
```
27
```

[42]:
```
# Make a copy of the dataframe
df_red = df.copy()
```

Downsize the larger categories

[43]:
```
for category in categories_to_reduce:
    # Get the original number of samples for this class
    original_count = category_counts[category]

    # Determine the number of samples to remove. This must not be more than the␣
↪original count
    num_articles_to_remove = original_count - max_articles_per_category

    # Randomly select articles to remove
    indices_to_remove = resample(
        df_red[df_red['category_red'] == category].index,
        replace=False,
        n_samples=num_articles_to_remove,
        random_state=12  # Set a seed for consistency
    )

    # Drop these indices from the dataframe
    df_red = df_red.drop(indices_to_remove)
```

[44]:
```
df_red['category_red'].value_counts()
```

```
[44]: BUSINESS & FINANCE    1656
      COMEDY                1656
      WEDDINGS              1656
      IMPACT                1656
      RELIGION              1656
      TRAVEL                1656
      QUEER VOICES          1656
      WELLNESS              1656
      WOMEN                 1656
      HOME & LIVING         1656
      BLACK VOICES          1656
      MEDIA                 1656
      STYLE & BEAUTY        1656
      WORLD NEWS            1656
      DIVORCE               1656
      FOOD & DRINK          1656
      CRIME                 1656
      PARENTING             1656
      SCIENCE               1656
      EDUCATION             1656
      ENTERTAINMENT         1656
      WEIRD NEWS            1656
      ENVIRONMENT           1656
      SPORTS                1656
      POLITICS              1656
      ARTS & CULTURE        1656
      TECH                  1656
      GOOD NEWS             1397
      FIFTY                 1396
      U.S. NEWS             1377
      LATINO VOICES         1130
      Name: category_red, dtype: int64
```

```
[45]: # Reset the indices after dataframe reduction
df_red.reset_index(drop=True, inplace=True)
```

The 31 classes have now been balanced very well, class imbalance is no longer an issue. The baseline models will be run to evaluate the performance.

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.

[46]:
```
import nltk
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer, WordNetLemmatizer
from sklearn.feature_extraction.text import TfidfVectorizer
```

[47]:
```
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
```

[48]:
```
# Install the necessary NLTK datasets if they are not in the environment yet.
# nltk.download('punkt')
# nltk.download('stopwords')
# nltk.download('wordnet')
```

[49]:
```
# Define the English language stopwords.
stop_words = set(stopwords.words('english'))

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

[50]:
```
# Display the English stopwords in the NLTK library
print(stop_words)
```

```
{'too', 'itself', 'when', 'ma', 'our', 'themselves', 'ain', 'out', 'am',
```

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

[51]:
```python
len(stop_words)
```

[51]:
```
179
```

NLTK's English stopwords library contains 179 words.

[52]:
```python
df.dtypes
```

[52]:
```
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
category_red                        object
dtype: object
```

[53]:
```python
# Make a contractions map:
# A contraction map will convert contracted words into two words
# which make more sense. Also, the apostrophes will be removed.
# Credit: This contraction map was obtained from the following source:
```

```python
# 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"
}
```

[54]:

```
# 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
```

[55]:
```
# 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 decrease 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
```

[56]:
```
# This is a modification from the preprocess_text function for preparation of␣
↪DistilBERT.
# The difference is that the replacing the punctuation with a space step has␣
↪been removed.
# DistilBERT considers punctuation in the sentence's context, so the␣
↪punctuation marks remain.
```

```
def preprocess_text_bert(text):
    # Convert the text to lowercase
    text = text.lower()
    # Call the expand contractions function
    ### It was found that this led to a minore decrease 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)
    # 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
```

[57]:
```
# 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()
```

[58]:
```
def process_column(df_red, column_name):
    # 1. Text Cleaning
    clean_text = df_red[column_name].apply(lambda x: preprocess_text(x))
```

```python
    # 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_red[processed_column_name] = [' '.join(words) for words in stemmed_words]

    return df_red, stemmed_words
```

[59]:
```
# Select the Headline column to process
#df_red, lemmatized_words = process_column(df_red, 'headline')
```

[60]:
```
# Plot a word cloud for the Headlines
#plot_word_cloud(lemmatized_words, 'Headlines')
```

[61]:
```
# Process the 'short description' column and plot the word cloud
#df_red, lemmatized_words = process_column(df_red, 'short_description')
```

[62]:
```
#plot_word_cloud(lemmatized_words, 'short_description')
```

[63]:
```
# Process the 'combined info' column and plot the word cloud
df_red, lemmatized_words = process_column(df_red, 'combined_info')
```

[64]:
```
#plot_word_cloud(lemmatized_words, 'combined_info')
```

[65]:
```
df_red['combined_info'][100]
```

[65]:
```
'U.S. Unemployment Claims Rise To Highest Level Since November Applications for
jobless aid climbed by 14,000 to 262,000 and now have risen five out of the last
six weeks, the Labor Department reported.'
```

[66]:
```
df_red['processed_combined_info'][100]
```

[66]:
```
'u unemploy claim rise highest level sinc novemb applic jobless aid climb 14 000
262 000 risen five last six week labor depart report'
```

Split the data into training and test sets

[67]:
```
df_red.head()
```

[67]:
```
                                                                link  \
0
https://www.huffpost.com/entry/covid-boosters-uptake-
us_n_632d719ee4b087fae6feaac9
1  https://www.huffpost.com/entry/american-airlines-passenger-banned-flight-
```

```
attendant-punch-justice-department_n_632e25d3e4b0e247890329fe
2                    https://www.huffpost.com/entry/amy-cooper-loses-
discrimination-lawsuit-franklin-templeton_n_632c6463e4b09d8701bd227e
3                             https://www.huffpost.com/entry/belk-worker-found-
dead-columbiana-centre-bathroom_n_632c5f8ce4b0572027b0251d
4   https://www.huffpost.com/entry/reporter-gets-adorable-surprise-from-her-
boyfriend-while-working-live-on-tv_n_632ccf43e4b0572027b10d74

    headline  \
0             Over 4 Million Americans Roll Up Sleeves For Omicron-Targeted
COVID Boosters
1  American Airlines Flyer Charged, Banned For Life After Punching Flight
Attendant On Video
2             Woman Who Called Cops On Black Bird-Watcher Loses Lawsuit Against
Ex-Employer
3                    Cleaner Was Dead In Belk Bathroom For 4 Days Before Body
Found: Police
4                         Reporter Gets Adorable Surprise From Her Boyfriend
While Live On TV

    category  \
0  U.S. NEWS
1  U.S. NEWS
2  U.S. NEWS
3  U.S. NEWS
4  U.S. NEWS

short_description  \
0          Health experts said it is too early to predict whether demand would
match up with the 171 million doses of the new boosters the U.S. ordered for the
fall.
1     He was subdued by passengers and crew when he fled to the back of the
aircraft after the confrontation, according to the U.S. attorney's office in Los
Angeles.
2        Amy Cooper accused investment firm Franklin Templeton of unfairly
firing her and branding her a racist after video of the Central Park encounter
went viral.
3  The 63-year-old woman was seen working at the South Carolina store on
Thursday. She was found dead Monday after her family reported her missing,
authorities said.
4                                              "Who's that behind you?" an anchor
for New York’s PIX11 asked journalist Michelle Ross as she finished up an
interview.

              authors       date  word_count_headline  \
0  Carla K. Johnson, AP 2022-09-23                   11
1        Mary Papenfuss 2022-09-23                   13
```

```
2        Nina Golgowski 2022-09-22                   11
3                       2022-09-22                   13
4         Elyse Wanshel 2022-09-22                   11

   word_count_description  \
0                      29
1                      28
2                      25
3                      26
4                      20

combined_info  \
0                     Over 4 Million Americans Roll Up Sleeves For Omicron-
Targeted COVID Boosters Health experts said it is too early to predict whether
demand would match up with the 171 million doses of the new boosters the U.S.
ordered for the fall.
1  American Airlines Flyer Charged, Banned For Life After Punching Flight
Attendant On Video He was subdued by passengers and crew when he fled to the
back of the aircraft after the confrontation, according to the U.S. attorney's
office in Los Angeles.
2                  Woman Who Called Cops On Black Bird-Watcher Loses Lawsuit
Against Ex-Employer Amy Cooper accused investment firm Franklin Templeton of
unfairly firing her and branding her a racist after video of the Central Park
encounter went viral.
3                   Cleaner Was Dead In Belk Bathroom For 4 Days Before Body
Found: Police The 63-year-old woman was seen working at the South Carolina store
on Thursday. She was found dead Monday after her family reported her missing,
authorities said.
4                                                                 Reporter Gets
Adorable Surprise From Her Boyfriend While Live On TV "Who's that behind you?"
an anchor for New York’s PIX11 asked journalist Michelle Ross as she finished up
an interview.

   word_count_combined  year  month category_red  \
0                   40  2022      9    U.S. NEWS
1                   41  2022      9    U.S. NEWS
2                   36  2022      9    U.S. NEWS
3                   39  2022      9    U.S. NEWS
4                   31  2022      9    U.S. NEWS

processed_combined_info
0           4 million american roll sleev omicron target covid booster health
expert said earli predict whether demand would match 171 million dose new
booster u order fall
1                              american airlin flyer charg ban life punch flight
attend video subdu passeng crew fled back aircraft confront accord u attorney
offic lo angel
```

```
2  woman call cop black bird watcher lose lawsuit ex employ ami cooper accus
invest firm franklin templeton unfairli fire brand racist video central park
encount went viral
3               cleaner dead belk bathroom 4 day bodi found polic 63 year old
woman seen work south carolina store thursday found dead monday famili report
miss author said
4                                                          report get ador
surpris boyfriend live tv behind anchor new york pix11 ask journalist michel
ross finish interview
```

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.

[68]:
```python
def remove_unique_words(df_red, column):
    # Extract all the words from all the speeches in the 'Processed_Text' column
    split_words = df_red[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_red[column] = col_without_unique
    return df_red
```

[69]:
```python
df_red = remove_unique_words(df_red, 'processed_combined_info')
```

```
word count: 34507
num unique words: 13685
```

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

[70]:
```
# 1. Split the data into training and test sets.
X_train, X_test, y_train, y_test =␣
 ↪train_test_split(df_red["processed_combined_info"],df_red["category_red"],test_size=0.
 ↪2,
                                                    stratify=df_red["category_red"],␣
 ↪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.

[71]:
```
# 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)
```

[72]:
```
# 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)
```

```
"""
```

[72]:
```
"\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

[73]:
```
# 3. Train the Naive-Bayes model
nb1 = MultinomialNB()
nb1.fit(X_train_vec, y_train)
```

[73]:
```
MultinomialNB()
```

[74]:
```
# 4. Evaluate the model
y_pred_nb1 = nb1.predict(X_test_vec)
```

[75]:

```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))
```

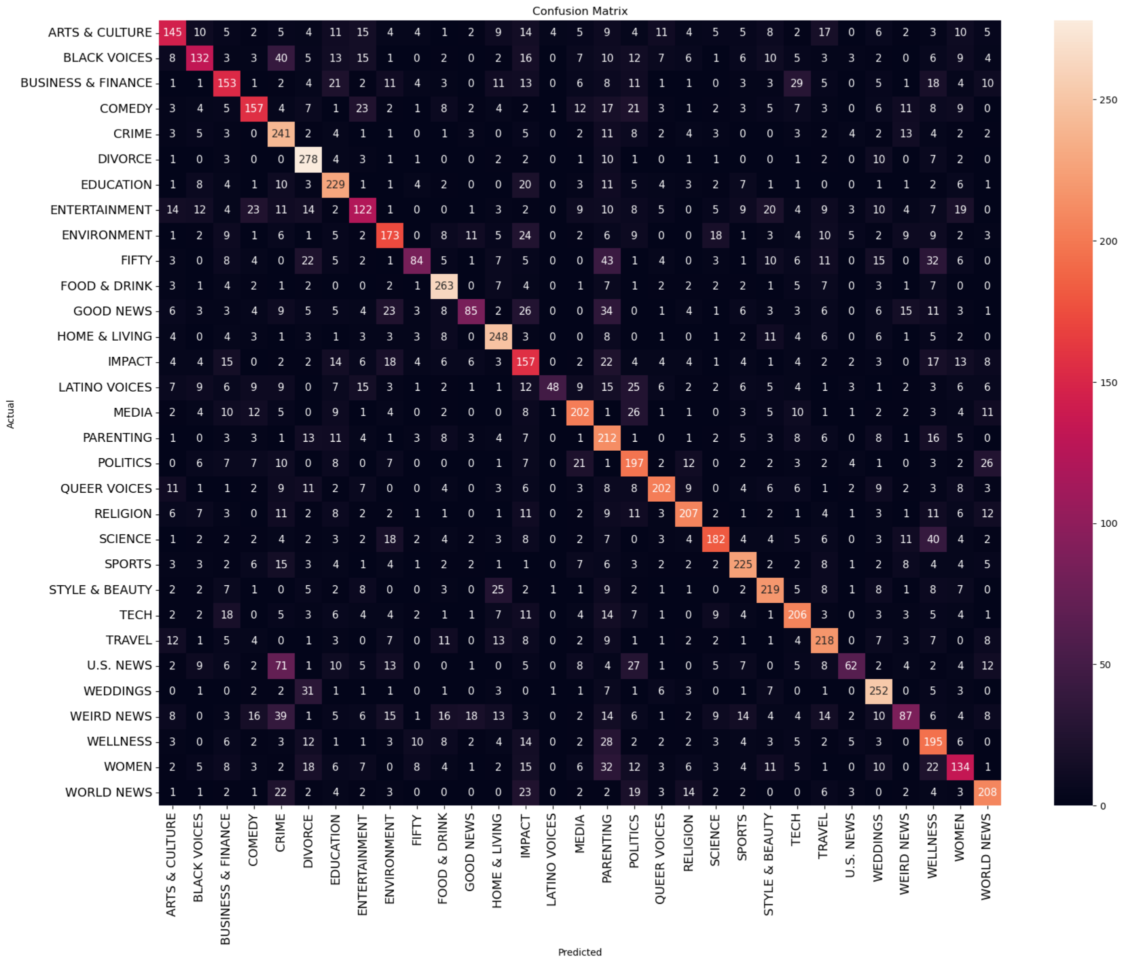
```
Accuracy: 55.21%

Classification Report:

                    precision    recall  f1-score   support

    ARTS & CULTURE       0.56      0.44      0.49       331
      BLACK VOICES       0.56      0.40      0.47       331
BUSINESS & FINANCE       0.49      0.46      0.48       332
            COMEDY       0.58      0.47      0.52       332
             CRIME       0.45      0.73      0.55       331
           DIVORCE       0.61      0.84      0.71       331
         EDUCATION       0.57      0.69      0.62       332
     ENTERTAINMENT       0.46      0.37      0.41       331
       ENVIRONMENT       0.53      0.52      0.53       331
             FIFTY       0.61      0.30      0.40       279
      FOOD & DRINK       0.69      0.79      0.74       331
         GOOD NEWS       0.60      0.30      0.40       280
     HOME & LIVING       0.65      0.75      0.69       331
            IMPACT       0.36      0.47      0.41       332
     LATINO VOICES       0.86      0.21      0.34       226
             MEDIA       0.62      0.61      0.62       331
         PARENTING       0.36      0.64      0.46       331
          POLITICS       0.45      0.60      0.52       331
      QUEER VOICES       0.71      0.61      0.66       331
          RELIGION       0.69      0.63      0.66       331
           SCIENCE       0.68      0.55      0.61       332
            SPORTS       0.67      0.68      0.67       331
    STYLE & BEAUTY       0.62      0.66      0.64       331
              TECH       0.59      0.62      0.60       331
            TRAVEL       0.58      0.66      0.62       331
         U.S. NEWS       0.61      0.22      0.33       276
          WEDDINGS       0.63      0.76      0.69       331
        WEIRD NEWS       0.47      0.26      0.34       331
          WELLNESS       0.41      0.59      0.49       331
             WOMEN       0.46      0.40      0.43       331
        WORLD NEWS       0.62      0.63      0.62       331

          accuracy                           0.55     10003
```

```
    macro avg       0.57      0.54      0.54     10003
 weighted avg       0.57      0.55      0.54     10003
```

For the Naive-Bayes model, with the addition of undersampling, there are no longer any classes that were never predicted. the overall accuracy has improved from 50.67% to 55.21%

Confusion Matrix

[76]:
```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": 11},
            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()
```



Summary of the Naive-Bayes Model

For the Naive-Bayes model, with the addition of undersampling, there are no longer any classes that were never predicted. the overall accuracy has improved from 50.67% to 55.21%.

Precision has fallen from 0.68 to 0.57, however there has been a large improvement in recall from 0.22 to 0.54. The F1-score has also improved from 0.23 to 0.54.

The real test is on the logistic regression model as it performed better on the baseline.

Logistic Regression Model

[77]:
```
# 3. Train the Logistic Regression model
lr1 = LogisticRegression(max_iter=600, random_state=12)
lr1.fit(X_train_vec, y_train)
```

[77]:
```
LogisticRegression(max_iter=600, random_state=12)
```

[78]:
```
# 4. Evaluate the model
y_pred_lr1 = lr1.predict(X_test_vec)
```

[79]:
```python
# Verify the predictions and test set label counts.
from collections import Counter

label_counts = Counter(y_pred_lr1)
print(label_counts)
```

```
Counter({'WELLNESS': 416, 'PARENTING': 416, 'FOOD & DRINK': 387, 'CRIME': 378,
'ENTERTAINMENT': 373, 'POLITICS': 370, 'HOME & LIVING': 368, 'TRAVEL': 368,
'SPORTS': 354, 'STYLE & BEAUTY': 353, 'WEIRD NEWS': 352, 'ARTS & CULTURE': 350,
'TECH': 345, 'WORLD NEWS': 344, 'BUSINESS & FINANCE': 342, 'MEDIA': 335,
'EDUCATION': 332, 'WEDDINGS': 327, 'SCIENCE': 325, 'DIVORCE': 323,
'ENVIRONMENT': 321, 'RELIGION': 316, 'WOMEN': 310, 'IMPACT': 309, 'BLACK
VOICES': 291, 'COMEDY': 277, 'QUEER VOICES': 269, 'FIFTY': 234, 'GOOD NEWS':
216, 'U.S. NEWS': 179, 'LATINO VOICES': 123})
```

[80]:
```python
label_counts2 = Counter(y_test)
print(label_counts2)
```

```
Counter({'SCIENCE': 332, 'IMPACT': 332, 'COMEDY': 332, 'BUSINESS & FINANCE':
332, 'EDUCATION': 332, 'QUEER VOICES': 331, 'ENTERTAINMENT': 331, 'WORLD NEWS':
331, 'SPORTS': 331, 'ARTS & CULTURE': 331, 'HOME & LIVING': 331, 'PARENTING':
331, 'ENVIRONMENT': 331, 'RELIGION': 331, 'STYLE & BEAUTY': 331, 'FOOD & DRINK':
331, 'CRIME': 331, 'TRAVEL': 331, 'WEDDINGS': 331, 'BLACK VOICES': 331,
'DIVORCE': 331, 'WOMEN': 331, 'TECH': 331, 'WEIRD NEWS': 331, 'POLITICS': 331,
'WELLNESS': 331, 'MEDIA': 331, 'GOOD NEWS': 280, 'FIFTY': 279, 'U.S. NEWS': 276,
'LATINO VOICES': 226})
```

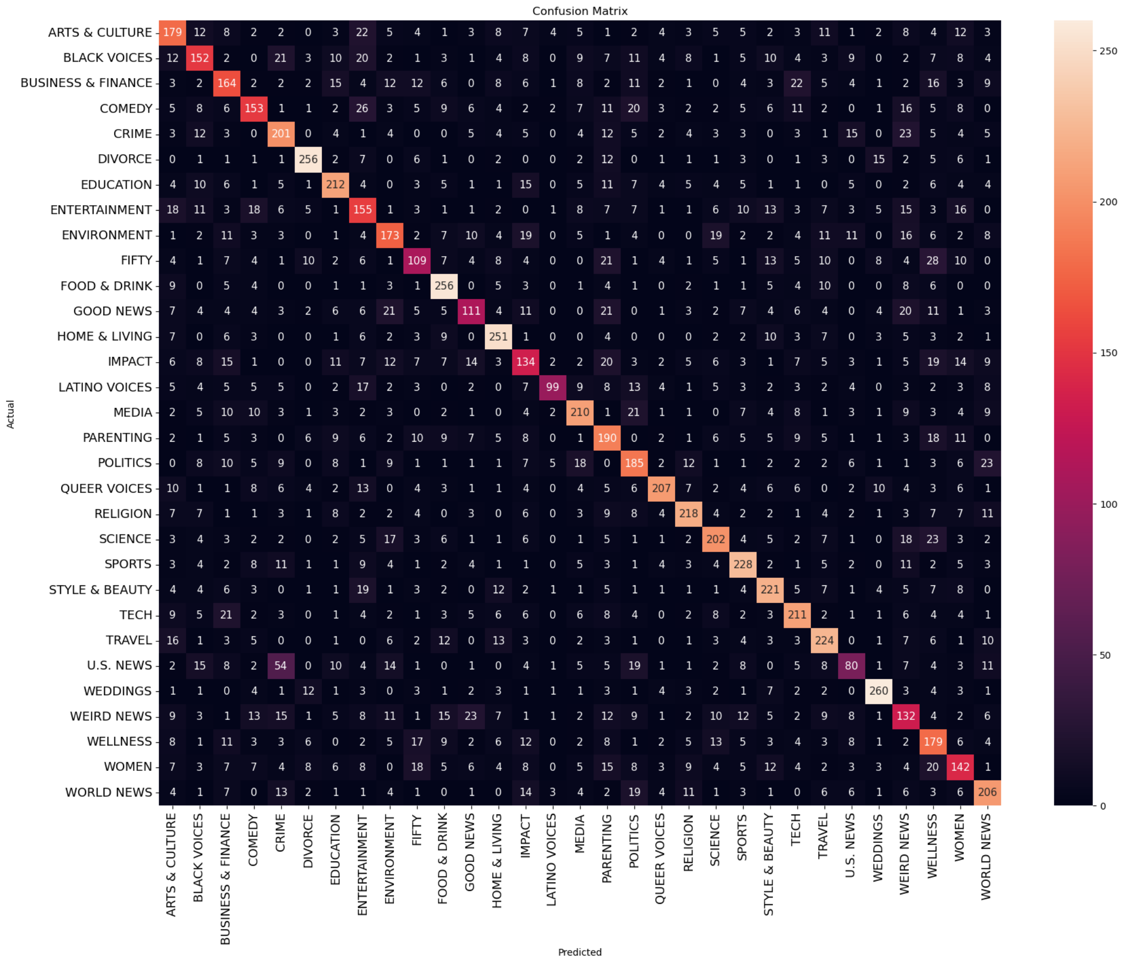
[81]:
```python
# Display the model's classififcation accuracy
accuracy = accuracy_score(y_test, y_pred_lr1)
print(f"Accuracy: {accuracy * 100:.2f}%")

# 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: 56.98%

Classification Report:

                    precision    recall  f1-score   support

    ARTS & CULTURE       0.51      0.54      0.53       331
      BLACK VOICES       0.52      0.46      0.49       331
BUSINESS & FINANCE       0.48      0.49      0.49       332
            COMEDY       0.55      0.46      0.50       332
             CRIME       0.53      0.61      0.57       331
           DIVORCE       0.79      0.77      0.78       331
         EDUCATION       0.64      0.64      0.64       332
```

```
ENTERTAINMENT       0.42      0.47      0.44       331
  ENVIRONMENT       0.54      0.52      0.53       331
        FIFTY       0.47      0.39      0.42       279
 FOOD & DRINK       0.66      0.77      0.71       331
    GOOD NEWS       0.51      0.40      0.45       280
HOME & LIVING       0.68      0.76      0.72       331
       IMPACT       0.43      0.40      0.42       332
LATINO VOICES       0.80      0.44      0.57       226
        MEDIA       0.63      0.63      0.63       331
    PARENTING       0.46      0.57      0.51       331
     POLITICS       0.50      0.56      0.53       331
 QUEER VOICES       0.77      0.63      0.69       331
     RELIGION       0.69      0.66      0.67       331
      SCIENCE       0.62      0.61      0.61       332
       SPORTS       0.64      0.69      0.67       331
STYLE & BEAUTY      0.63      0.67      0.65       331
         TECH       0.61      0.64      0.62       331
       TRAVEL       0.61      0.68      0.64       331
    U.S. NEWS       0.45      0.29      0.35       276
     WEDDINGS       0.80      0.79      0.79       331
   WEIRD NEWS       0.38      0.40      0.39       331
     WELLNESS       0.43      0.54      0.48       331
        WOMEN       0.46      0.43      0.44       331
   WORLD NEWS       0.60      0.62      0.61       331

     accuracy                           0.57     10003
    macro avg       0.57      0.57      0.57     10003
 weighted avg       0.57      0.57      0.57     10003
```

[82]:

```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": 11},
            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()
```



Summary of the Logistic Regression Model

The results were encouraging for the Naive-Bayes model, however for the Logistc Regressor, the results were not favourable. The overall accuracy fell from 66.76% down to 56.98%. This is large degradation of almost 10%.

Precision has fallen from 0.63 to 0.57, however there has been a slight improvement in recall from 0.50 to 0.57. The F1-score has also improved from 0.54 to 0.57.

2.2.1 Conclusion of Undersampling

It is interesting to see how the results were so different for the two baseline models. The logistic regression model clearly had the best results in the baseline and also for the reduced number of categories (refer to the main notebook). As its best performance was better, I have decided to not include undersampling before evaluating the neural network models.

It can be concluded that there were improvements in predicting the minority classes, but this has drastically affected the overall accuracy. Clearly, the larger amount of training data is very beneficial to a dataset like this where there is a large number of additional words and variability for the models to learn from. As there are no critical categories and accurately classifying any particular category is no more important than any other, it can be concluded that utilising the full dataset is clearly more advantageous to build an overall more accurate model than having a fairly balanced dataset. SMOTE is a viable option worthy of exploration, but due to the much larger processing times required, it is not an option that can be explored.

This project will not implement undersampling!

[ ]:

```

```