West_Group_2_NLP_Project

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1 West 2 Group - NLP Project

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1.0.1 Table of Contents

1.1 Getting the Data

1.1.1 Library Imports

[5]:
```
#standard library imports
import pandas as pd
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
import circlify
```

```python
import time

from sklearn.metrics import accuracy_score, classification_report, f1_score
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.datasets import fetch_20newsgroups


from sklearn.decomposition import TruncatedSVD
from sklearn.feature_extraction.text import TfidfVectorizer
import nltk
from nltk.corpus import stopwords
from collections import Counter
from nltk.tokenize import word_tokenize
from nltk import ngrams


#simple models
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier

#TensorFlow / Keras functions
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense, Flatten, SimpleRNN, LSTM, GRU, \
  Embedding, TextVectorization, Flatten, Dropout, GlobalAveragePooling1D, \
    Conv1D
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.metrics import Precision, Recall
from tensorflow.keras.callbacks import EarlyStopping





#HTML and regex for cleaning
from bs4 import BeautifulSoup
import re

from wordcloud import WordCloud

#sentiment Analysis
from nltk.sentiment import SentimentIntensityAnalyzer
```

[6]:
```python
#in the event a package is not downloaded
# import nltk
# nltk.download('stopwords')
```

[7]:
```python
#data import from provided code
import tensorflow_datasets as tfds
train_data, test_data = tfds.load(
  'ag_news_subset',
  split = ['train', 'test'],
  batch_size = -1
)
df_train = pd.DataFrame(train_data)
df_test = pd.DataFrame(test_data)
```

[8]:
```python
df_train.shape
```

[8]:
```
(120000, 3)
```

[9]:
```python
df_test.shape
```

[9]:
```
(7600, 3)
```

[10]:
```python
df_train.head()
```

[10]:
```
                                         description  label  \
0  b'AMD #39;s new dual-core Opteron chip is desi…      3
1  b'Reuters - Major League Baseball\\Monday anno…      1
2  b'President Bush #39;s  quot;revenue-neutral q…      2
3  b'Britain will run out of leading scientists u…      3
4  b'London, England (Sports Network) - England m…      1

                                         title
0       b'AMD Debuts Dual-Core Opteron Processor'
1           b"Wood's Suspension Upheld (Reuters)"
2  b'Bush reform may have blue states seeing red'
3            b"'Halt science decline in schools'"
4                      b'Gerrard leaves practice'
```

1.1.2 Labels

0 - World News

1 - Sports

2 - Business

3 - Science/Technology

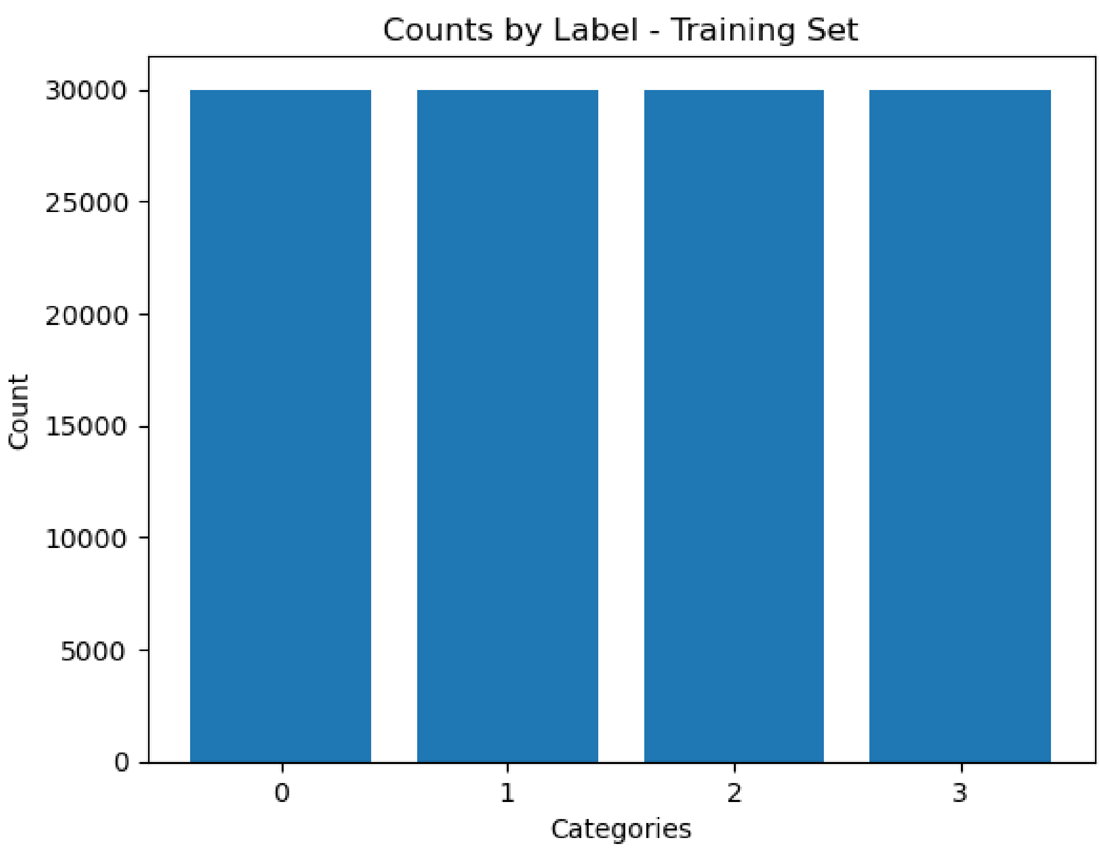
[11]:
```python
#looking at example
df_train.iloc[1,]
```

[11]:
```
description    b'Reuters - Major League Baseball\\Monday anno…
label                                                        1
title                       b"Wood's Suspension Upheld (Reuters)"
Name: 1, dtype: object
```

[12]:
```python
#more specific example
df_train.iloc[4,]['description']
```

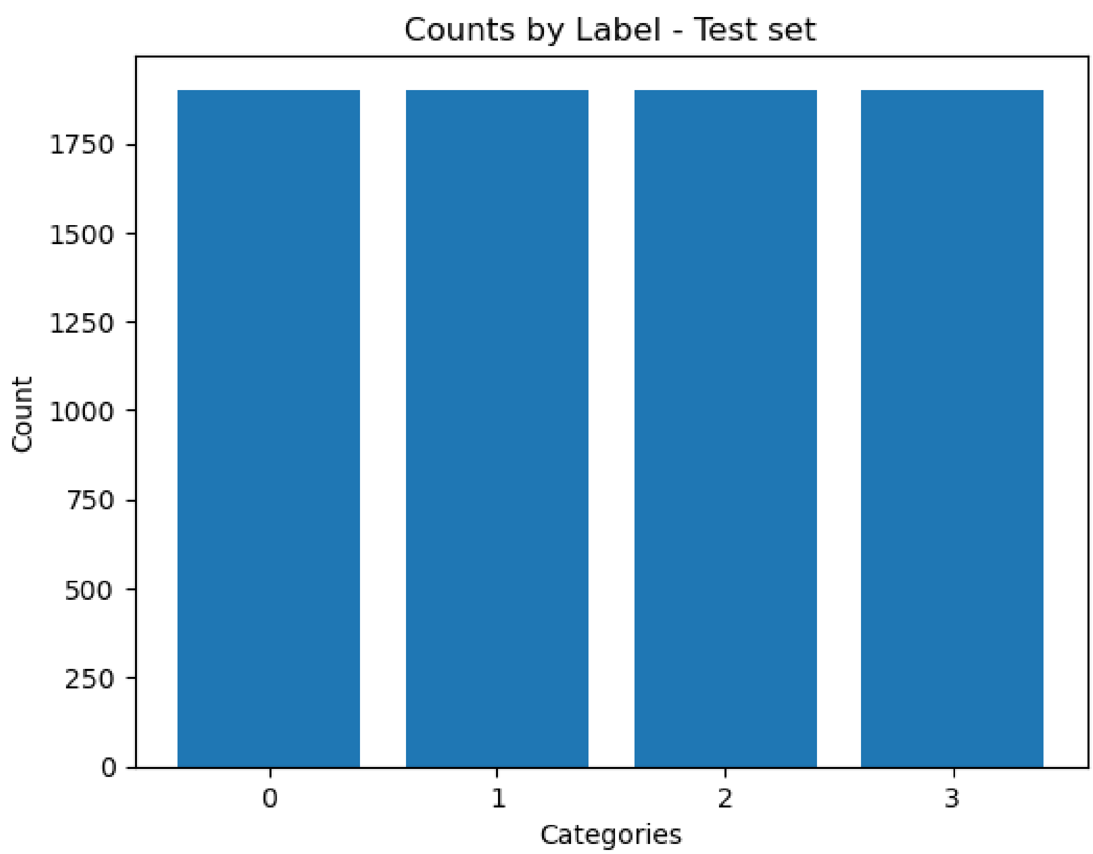
[12]:
```
b'London, England (Sports Network) - England midfielder Steven Gerrard injured
his groin late in Thursday #39;s training session, but is hopeful he will be
ready for Saturday #39;s World Cup qualifier against Austria.'
```

[13]:
```python
#plot bar chart of training set article labels
plt.bar(df_train['label'].unique(), df_train['label'].value_counts())

#labels and title
plt.xlabel('Categories')
plt.xticks(df_train['label'].unique())
plt.ylabel('Count')
plt.title('Counts by Label - Training Set')

plt.show()
```



- From the plot we can see that all the categories are evenly split at 30,000 each in the training set

[14]:
```
#plot bar chart of  test set article labels
plt.bar(df_test['label'].unique(), df_test['label'].value_counts())

#labels and title
plt.xlabel('Categories')
plt.xticks(df_test['label'].unique())
plt.ylabel('Count')
plt.title('Counts by Label - Test set')

plt.show()
```



- Each article count in the test set has 1900

1.2 EDA

Before conducting EDA we knew that the success or failure of the model(s) would come down to the differences in the words, and their frequenices, within each type of article.

1.2.1 Clean Text

- To clean the text, we need to first get the text out of html format. We need to also remove all puncuation. There won't be anything learned from this, and if anything, puncuation will throw off the model as the words could be combined or treated as different words if they are hypenated, inside of quotes, or capitilzied. We will also shift all words to lowercase.
- After those steps, we also need to remove traces of "39s". This is an html error that came from "#39;s" which was a in the place of all apostrophes.
- We also will remove stop words from the descriptions in order to provide more meaningful words.

[15]:
```
#function to convert a raw text from loaded dataset to string

#removes all non-letters
# '[^a-zA-Z]', ' '

#removes all punctuation
#r'[^\w\s\d]'

#removes all punctuation, but leaves punctuation between numbers
#r'(?<=\d)[^\w\s\d]|[^\w\s\d](?=\d)'

def clean_words(raw_description):

    #remove HTML
    description_text = BeautifulSoup(raw_description).get_text()

    #EVALUATE*************
    #remove non-letters
    # letters_only = re.sub(r'[^a-zA-Z]', '', review_text)

    #remove puncuation
    no_punct = re.sub(r'[^\w\s\d]', '', description_text)

    #removing html artifact 39s from when apostrophe errored
    final_clean = re.sub(r'39s', '', no_punct)

    #convert to lower case, split into individual words.
    words = final_clean.lower().split()

    #setting stop words
    stops = set(stopwords.words('english'))
```

```
    #remove stop words.
    meaningful_words = [w for w in words if w not in stops]

    #join the words into one string, return result.
    return(" ".join(meaningful_words))
```

[16]:
```
#timing how long it takes to clean desriptions
start_time = time.time()

#applying function over description column creating new column
df_train['cleaned_description'] = df_train['description'].apply(clean_words)

end_time = time.time()
```

```
/var/folders/9l/8vvnk63j2j9f_hg8yf6z57v80000gn/T/ipykernel_5904/3636424674.py:15
: MarkupResemblesLocatorWarning: The input looks more like a filename than
markup. You may want to open this file and pass the filehandle into Beautiful
Soup.
  description_text = BeautifulSoup(raw_description).get_text()
```

[17]:
```
df_train
```

[17]:
```
                                              description  label  \
0       b'AMD #39;s new dual-core Opteron chip is desi…      3
1       b'Reuters - Major League Baseball\\Monday anno…      1
2       b'President Bush #39;s  quot;revenue-neutral q…      2
3       b'Britain will run out of leading scientists u…      3
4       b'London, England (Sports Network) - England m…      1
…                                                     …    …
119995  b'Ivan Ljubicic edged No. 7 seed Joachim Johan…      1
119996  b'MANAMA: A \\$1.3 billion (BD491 million) com…      2
119997  b'And lo, the hawk begat the dove. At least th…      0
119998  b'West Palm Beach, FL (Sports Network) - Tom L…      1
119999  b'If the Federal Communications Commission has…      2

                                                    title  \
0               b'AMD Debuts Dual-Core Opteron Processor'
1                   b"Wood's Suspension Upheld (Reuters)"
2          b'Bush reform may have blue states seeing red'
3                    b"'Halt science decline in schools'"
4                              b'Gerrard leaves practice'
…                                                     …
119995       b'Agassi, Ljubicic advance in Madrid Masters'
119996  b'\\$1.3 billion power plant will generate 3,5…
119997                               b'Last man standing'
119998          b'Report: Lehman named Ryder Cup captain'
119999  b'Got digital? By end of  #39;06, you may not …
```

```
                                       cleaned_description
0       amd new dualcore opteron chip designed mainly …
1       reuters major league baseballmonday announced …
2       president bush quotrevenueneutral quot tax ref…
3       britain run leading scientists unless science …
4       london england sports network england midfield…
…                                                    …
119995  ivan ljubicic edged 7 seed joachim johansson t…
119996  manama 13 billion bd491 million combined power…
119997  lo hawk begat dove least one imagines private …
119998  west palm beach fl sports network tom lehman n…
119999  federal communications commission way every am…

[120000 rows x 4 columns]
```

[18]:
```
elapsed_time = end_time - start_time
print(f"cleaning training set descriptions time: {elapsed_time:.4f} seconds")
```

```
cleaning training set descriptions time: 11.5899 seconds
```

[19]:
```
#time for cleaning titles
start_time = time.time()

#applying function over description column creating new column
df_train['cleaned_title'] = df_train['title'].apply(clean_words)

end_time = time.time()
```

```
/var/folders/9l/8vvnk63j2j9f_hg8yf6z57v80000gn/T/ipykernel_5904/3636424674.py:15
: MarkupResemblesLocatorWarning: The input looks more like a filename than
markup. You may want to open this file and pass the filehandle into Beautiful
Soup.
  description_text = BeautifulSoup(raw_description).get_text()
```

[20]:
```
df_train
```

[20]:
```
                                               description  label  \
0       b'AMD #39;s new dual-core Opteron chip is desi…      3
1       b'Reuters - Major League Baseball\\Monday anno…      1
2       b'President Bush #39;s  quot;revenue-neutral q…      2
3       b'Britain will run out of leading scientists u…      3
4       b'London, England (Sports Network) - England m…      1
…                                                    …    …
119995  b'Ivan Ljubicic edged No. 7 seed Joachim Johan…      1
119996  b'MANAMA: A \\$1.3 billion (BD491 million) com…      2
119997  b'And lo, the hawk begat the dove. At least th…      0
119998  b'West Palm Beach, FL (Sports Network) - Tom L…      1
```

```
119999  b'If the Federal Communications Commission has…      2

                                                    title  \
0                 b'AMD Debuts Dual-Core Opteron Processor'
1                     b"Wood's Suspension Upheld (Reuters)"
2            b'Bush reform may have blue states seeing red'
3                      b"'Halt science decline in schools'"
4                                b'Gerrard leaves practice'
…                                                     …
119995       b'Agassi, Ljubicic advance in Madrid Masters'
119996  b'\\$1.3 billion power plant will generate 3,5…
119997                                b'Last man standing'
119998            b'Report: Lehman named Ryder Cup captain'
119999  b'Got digital? By end of  #39;06, you may not …

                                       cleaned_description  \
0       amd new dualcore opteron chip designed mainly …
1       reuters major league baseballmonday announced …
2       president bush quotrevenueneutral quot tax ref…
3       britain run leading scientists unless science …
4       london england sports network england midfield…
…                                                     …
119995  ivan ljubicic edged 7 seed joachim johansson t…
119996  manama 13 billion bd491 million combined power…
119997  lo hawk begat dove least one imagines private …
119998  west palm beach fl sports network tom lehman n…
119999  federal communications commission way every am…

                                   cleaned_title
0            amd debuts dualcore opteron processor
1                  woods suspension upheld reuters
2           bush reform may blue states seeing red
3                     halt science decline schools
4                          gerrard leaves practice
…                                             …
119995         agassi ljubicic advance madrid masters
119996  13 billion power plant generate 3500 jobs
119997                          last man standing
119998        report lehman named ryder cup captain
119999            got digital end 3906 may choice

[120000 rows x 5 columns]
```

1.2.2 Split info Seperate Article Label DFs

[21]:
```
#0 - World News
world_news_df_train = df_train[df_train['label']==0]

world_news_df_train.shape
```

[21]: (30000, 5)

[22]:
```
#1 - Sports
sports_df_train = df_train[df_train['label']==1]

sports_df_train.shape
```

[22]: (30000, 5)

[23]:
```
#2 - Business
business_df_train = df_train[df_train['label']==2]

business_df_train.shape
```

[23]: (30000, 5)

[24]:
```
#3 - Science/Tech
science_df_train = df_train[df_train['label']==3]

science_df_train.shape
```

[24]: (30000, 5)

1.2.3 Creating datasets of words

[25]:
```
def word_counts_df(texts):
    #tokenize the texts into words
    tokenized_texts = [word_tokenize(text) for text in texts]

    #count the occurrences of each word
    word_counts_list = [Counter(tokens) for tokens in tokenized_texts]

    #merge all the counters into one
    total_word_counts = sum(word_counts_list, Counter())

    #create a DataFrame from the merged counters
    word_counts_df = pd.DataFrame(list(total_word_counts.items()),␣
↪columns=['Word', 'Count'])

    return word_counts_df
```

[26]:
```python
world_news_words = word_counts_df(world_news_df_train['cleaned_description'])
```

[27]:
```python
world_news_words.head()
```

[27]:

	Word	Count
0	tokyo	345
1	sony	8
2	corp	84
3	banking	15
4	3	72

[28]:
```python
sports_words = word_counts_df(sports_df_train['cleaned_description'])
```

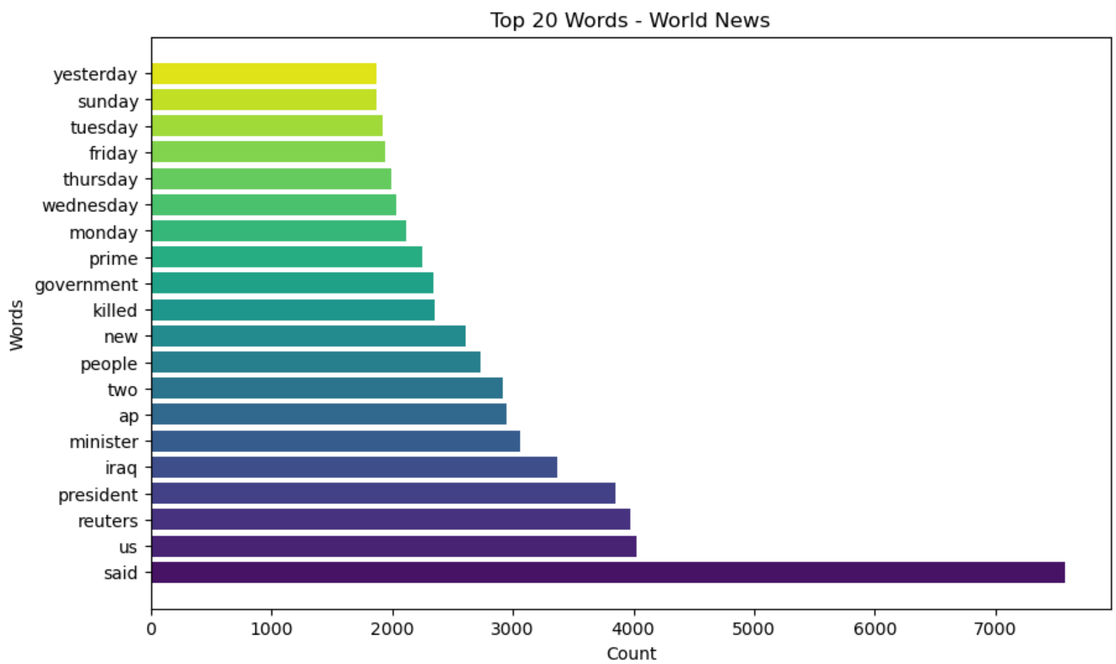
[29]:
```python
business_words = word_counts_df(business_df_train['cleaned_description'])
```

[30]:
```python
science_tech_words = word_counts_df(science_df_train['cleaned_description'])
```

Plotting most frequent words

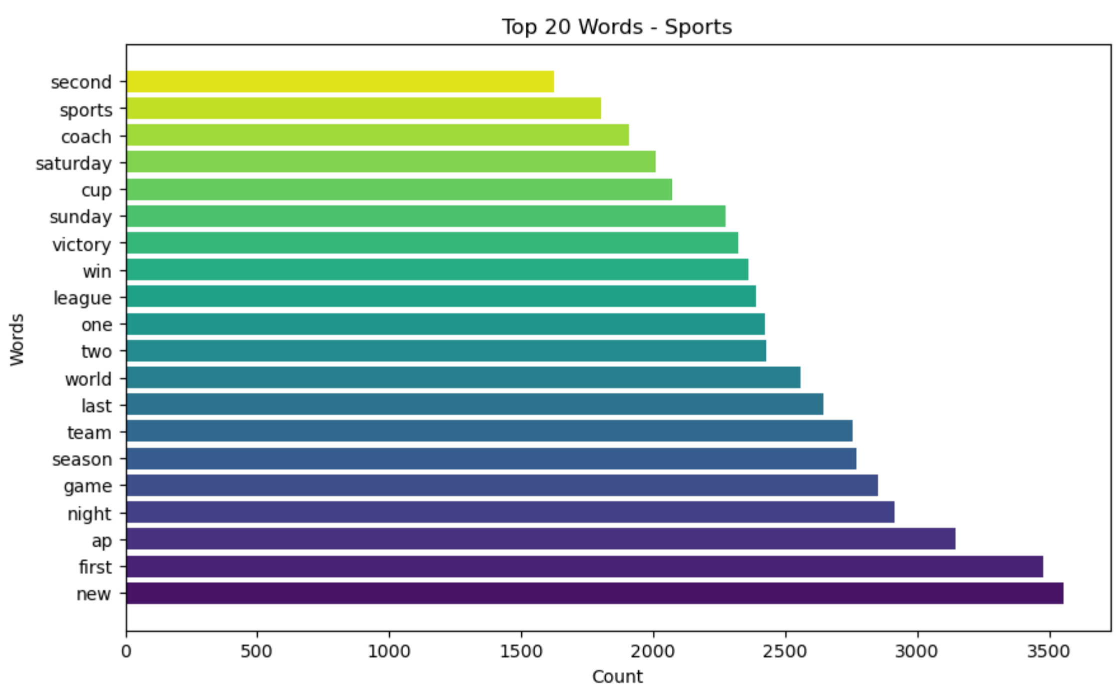
[31]:
```python
#creating function to plot the top words from each article label df
def plot_top_words(word_counts_df, top_n=10, df_name = "ENTER DF NAME"):
    #select the top number of words
    top_words_df = word_counts_df.sort_values(by='Count', ascending=False).
 ↪head(top_n)

    #use a color palette for the bars
    colors = sns.color_palette("viridis", n_colors=top_n)

    #plot horizontal bar chart
    plt.figure(figsize=(10, 6))
    plt.barh(top_words_df['Word'], top_words_df['Count'], color=colors)
    plt.xlabel('Count')
    plt.ylabel('Words')
    plt.title(f'Top {top_n} Words - {df_name}')
    plt.show()
```

[32]:
```python
#plotting world news top words
plot_top_words(world_news_words, top_n=20, df_name="World News")
```



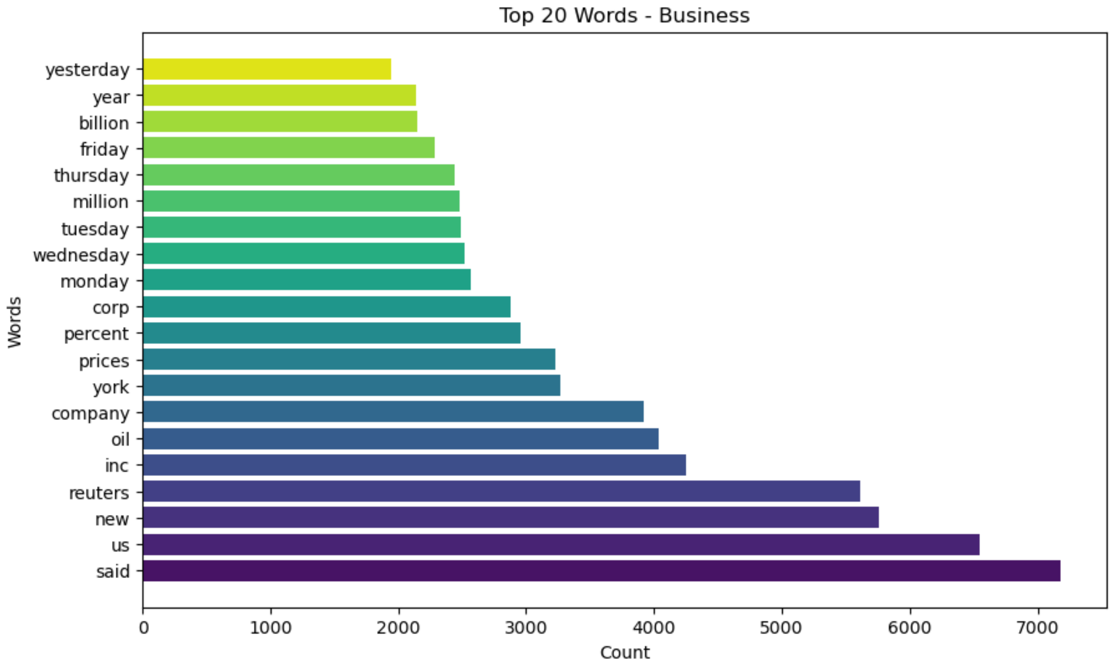
prime, government, killed, people, minister, iraq, president

[33]:
```
#plotting top sports words
plot_top_words(sports_words, top_n=20, df_name="Sports")
```



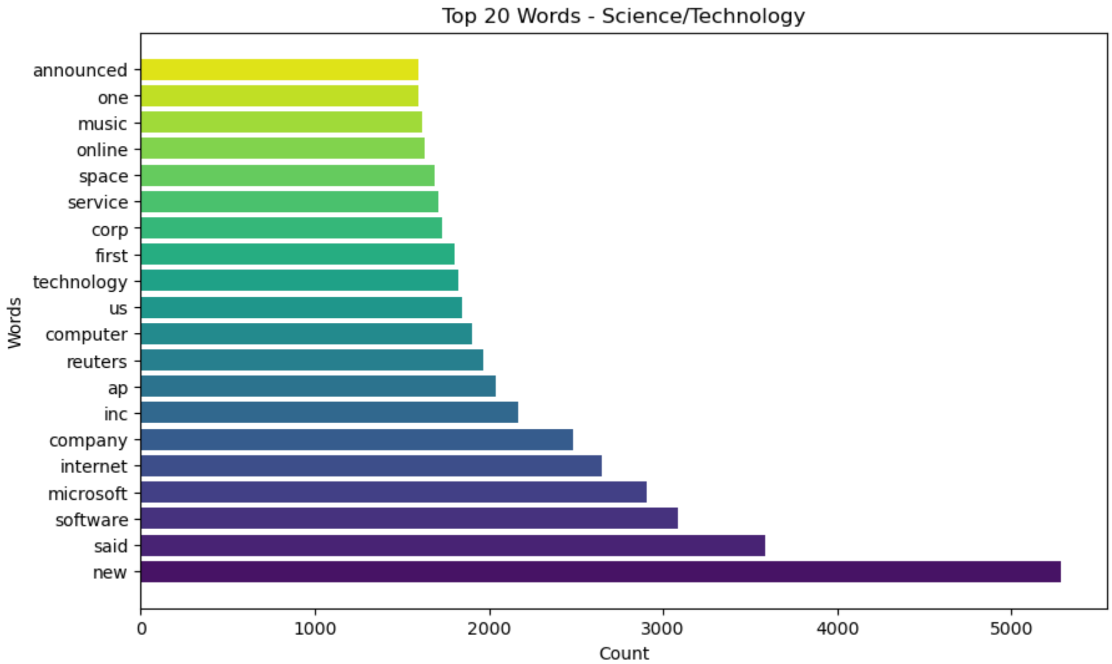
[34]:

```
#plotting top business words
plot_top_words(business_words, top_n=20, df_name="Business")
```



[35]:

```
#plotting top science/technology words
plot_top_words(science_tech_words, top_n=20, df_name="Science/Technology")
```



There are some differences between the types of articles and the top words. World News unique words - prime, government, killed, people, minister, iraq, president

Sports unique words - sport, coach, win, cup, team, season

Business unique words - million, crop, prices, york

Science/Technology unique words - announced, online, space, technology, computer

Words that are similar across all types of articles - said, new, - several days of the week were top words in the World News, Sports, and Business articles

It might be worth removing the words that are frequent and appear in most of the article types

1.2.4 Circle Plots

[36]:
```
#pip install circlify
```

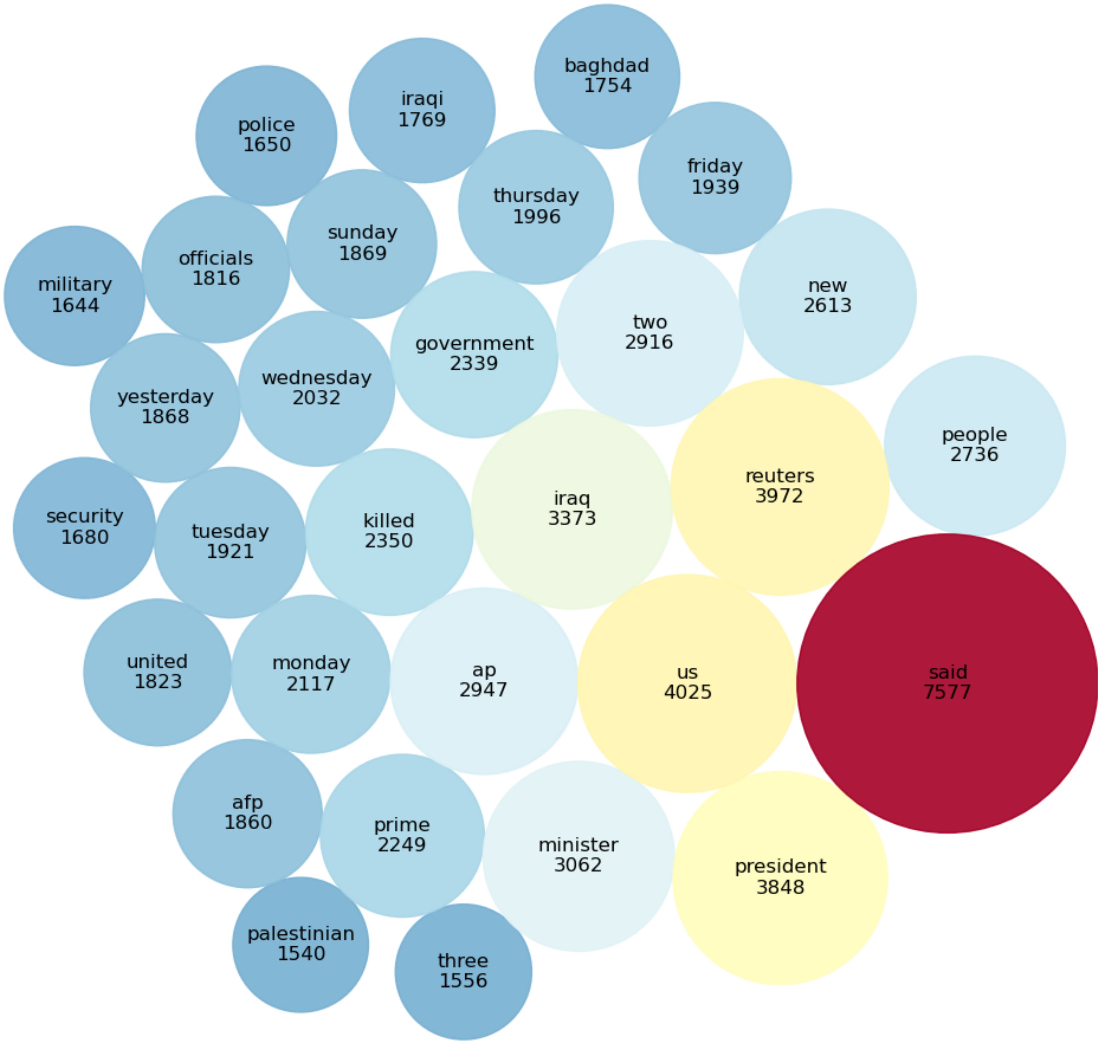
[37]:
```
#create function to get a color dictionary
def get_colordict(palette,number,start):
    pal = list(sns.color_palette(palette=palette, n_colors=number).as_hex())
    color_d = dict(enumerate(pal, start=start))
    return color_d
```

World News Circles

[38]:
```
# compute circle positions:
```

```
circles = circlify.circlify(world_news_words.sort_values(by='Count',␣
 ↪ascending=False)['Count'][0:30].tolist(),
                            show_enclosure=False,
                            target_enclosure=circlify.Circle(x=0, y=0))
# n = world_news_words['Count'][0:30].max()
n = world_news_words.sort_values(by='Count', ascending=False)['Count'][0:30].
 ↪max()
color_dict = get_colordict('RdYlBu_r',n ,1)
```

[39]:
```
fig, ax = plt.subplots(figsize=(12,12), facecolor='white')
ax.axis('off')
lim = max(max(abs(circle.x)+circle.r, abs(circle.y)+circle.r,) for circle in␣
 ↪circles)
plt.xlim(-lim, lim)
plt.ylim(-lim, lim)

# list of labels
labels = list(world_news_words.sort_values(by='Count',␣
 ↪ascending=False)['Word'][0:30])
counts = list(world_news_words.sort_values(by='Count',␣
 ↪ascending=False)['Count'][0:30])
labels.reverse()
counts.reverse()

#print circles
for circle, label, count in zip(circles, labels, counts):
    x, y, r = circle
    ax.add_patch(plt.Circle((x, y), r, alpha=0.9, color = color_dict.
 ↪get(count)))
    plt.annotate(label +'\n'+ str(count), (x,y), size=12, va='center',␣
 ↪ha='center')
plt.xticks([])
plt.yticks([])
plt.show()
```

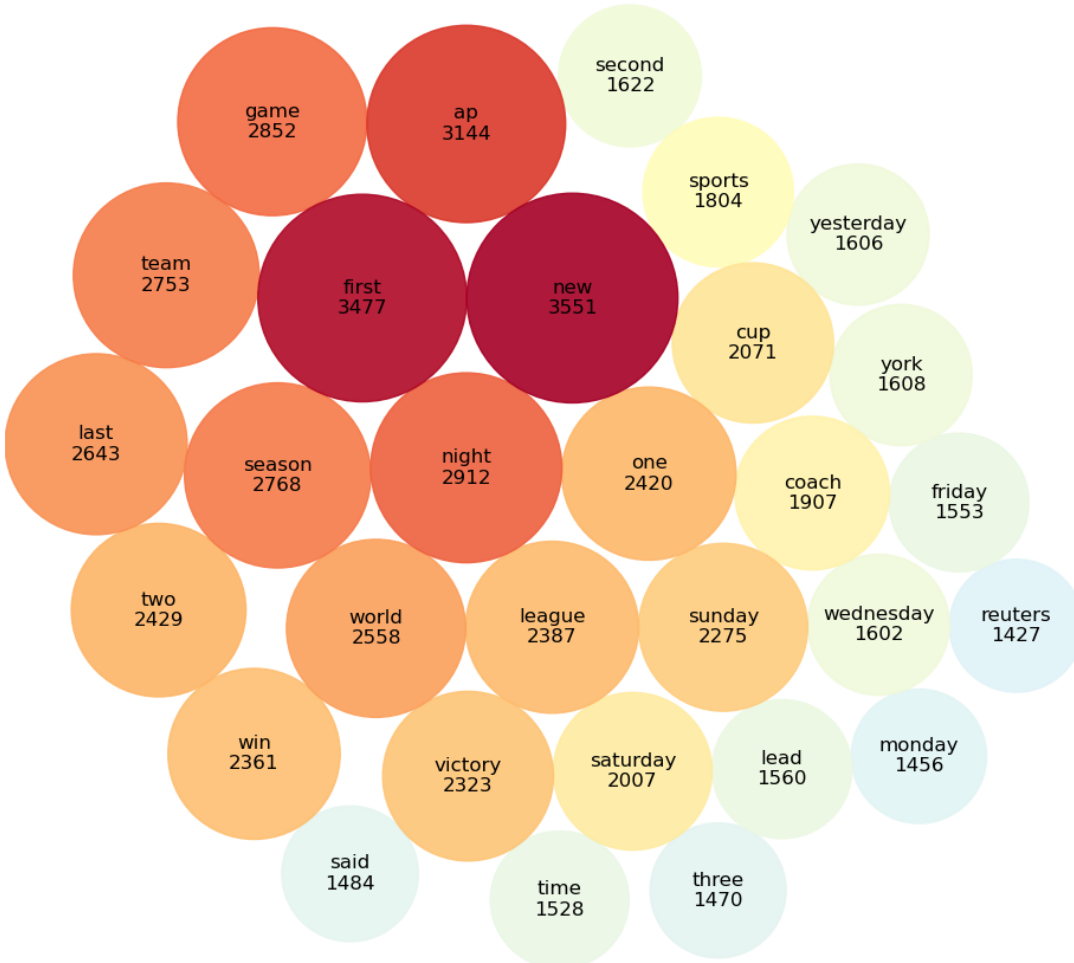


Sports Circles

[40]:
```
# compute circle positions:
circles = circlify.circlify(sports_words.sort_values(by='Count',␣
    ↪ascending=False)['Count'][0:30].tolist(),
                             show_enclosure=False,
                             target_enclosure=circlify.Circle(x=0, y=0))
# n = world_news_words['Count'][0:30].max()
n = sports_words.sort_values(by='Count', ascending=False)['Count'][0:30].max()
color_dict = get_colordict('RdYlBu_r',n ,1)
```

[41]:
```
fig, ax = plt.subplots(figsize=(12,12), facecolor='white')
ax.axis('off')
```

```
lim = max(max(abs(circle.x)+circle.r, abs(circle.y)+circle.r,) for circle in␣
↪circles)
plt.xlim(-lim, lim)
plt.ylim(-lim, lim)

# list of labels
labels = list(sports_words.sort_values(by='Count', ascending=False)['Word'][0:
↪30])
counts = list(sports_words.sort_values(by='Count', ascending=False)['Count'][0:
↪30])
labels.reverse()
counts.reverse()

#print circles
for circle, label, count in zip(circles, labels, counts):
    x, y, r = circle
    ax.add_patch(plt.Circle((x, y), r, alpha=0.9, color = color_dict.
↪get(count)))
    plt.annotate(label +'\n'+ str(count), (x,y), size=12, va='center',␣
↪ha='center')
plt.xticks([])
plt.yticks([])
plt.show()
```

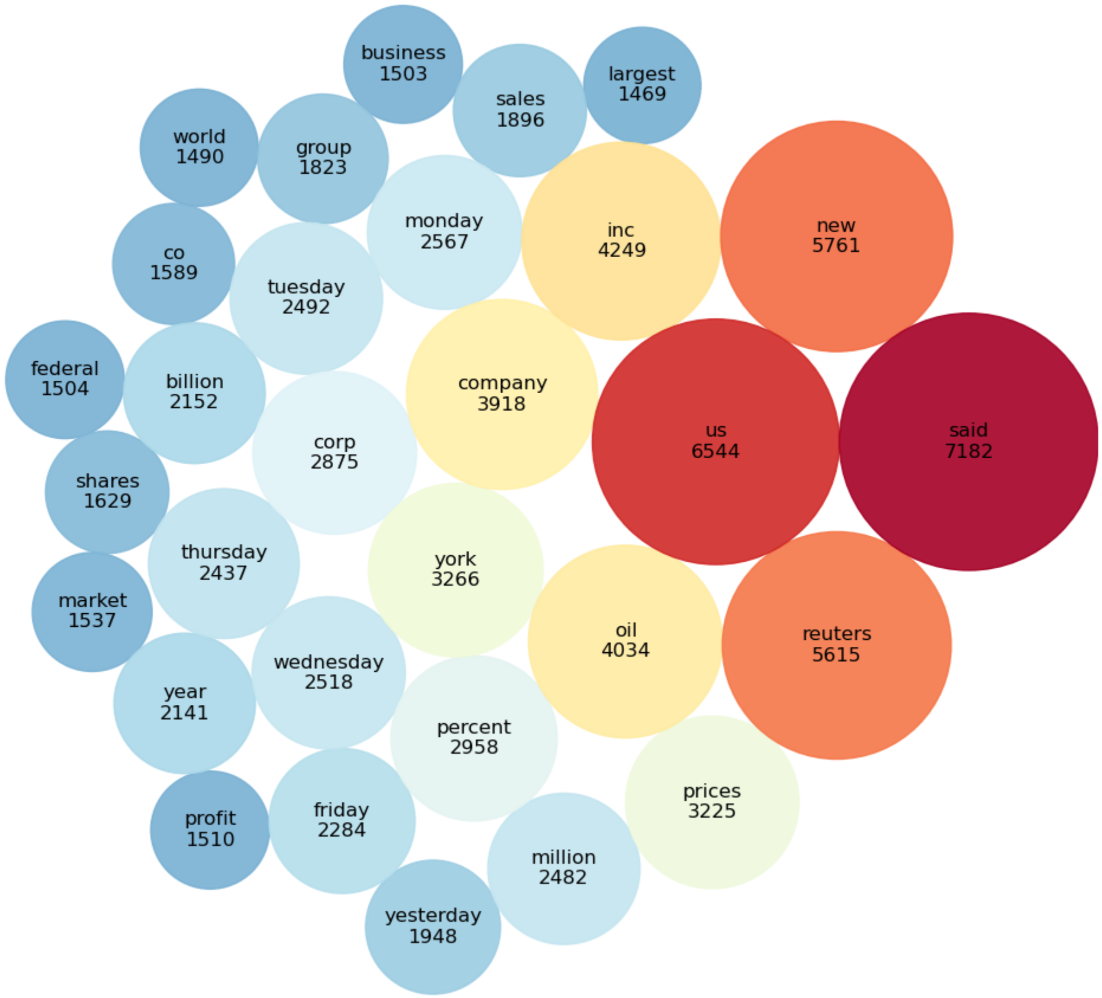


Business Circles

[42]:
```
# compute circle positions:
circles = circlify.circlify(business_words.sort_values(by='Count',␣
↪ascending=False)['Count'][0:30].tolist(),
                            show_enclosure=False,
                            target_enclosure=circlify.Circle(x=0, y=0))

n = business_words.sort_values(by='Count', ascending=False)['Count'][0:30].max()
color_dict = get_colordict('RdYlBu_r',n ,1)
```

[43]:
```
fig, ax = plt.subplots(figsize=(12,12), facecolor='white')
ax.axis('off')
```

```python
lim = max(max(abs(circle.x)+circle.r, abs(circle.y)+circle.r,) for circle in␣
↪circles)
plt.xlim(-lim, lim)
plt.ylim(-lim, lim)

# list of labels
labels = list(business_words.sort_values(by='Count', ascending=False)['Word'][0:
↪30])
counts = list(business_words.sort_values(by='Count',␣
↪ascending=False)['Count'][0:30])
labels.reverse()
counts.reverse()

#print circles
for circle, label, count in zip(circles, labels, counts):
    x, y, r = circle
    ax.add_patch(plt.Circle((x, y), r, alpha=0.9, color = color_dict.
↪get(count)))
    plt.annotate(label +'\n'+ str(count), (x,y), size=12, va='center',␣
↪ha='center')
plt.xticks([])
plt.yticks([])
plt.show()
```

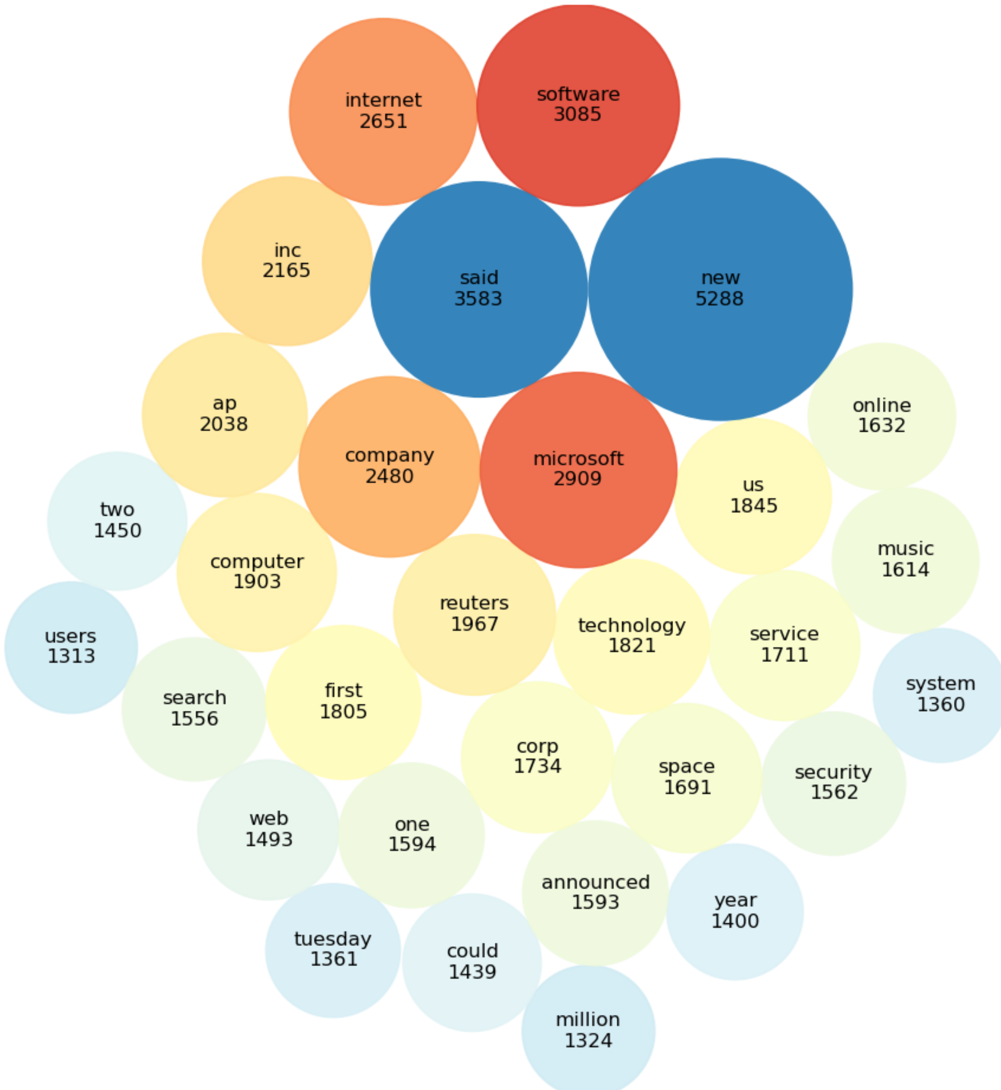


Science/Technology Circles

[44]:
```
# compute circle positions:
circles = circlify.circlify(science_tech_words.sort_values(by='Count',␣
 ↪ascending=False)['Count'][0:30].tolist(),
                            show_enclosure=False,
                            target_enclosure=circlify.Circle(x=0, y=0))

n = sports_words.sort_values(by='Count', ascending=False)['Count'][0:30].max()
color_dict = get_colordict('RdYlBu_r',n ,1)
```

[45]:
```
fig, ax = plt.subplots(figsize=(12,12), facecolor='white')
ax.axis('off')
```

```
lim = max(max(abs(circle.x)+circle.r, abs(circle.y)+circle.r,) for circle in␣
↪circles)
plt.xlim(-lim, lim)
plt.ylim(-lim, lim)

# list of labels
labels = list(science_tech_words.sort_values(by='Count',␣
↪ascending=False)['Word'][0:30])
counts = list(science_tech_words.sort_values(by='Count',␣
↪ascending=False)['Count'][0:30])
labels.reverse()
counts.reverse()

#print circles
for circle, label, count in zip(circles, labels, counts):
    x, y, r = circle
    ax.add_patch(plt.Circle((x, y), r, alpha=0.9, color = color_dict.
↪get(count)))
    plt.annotate(label +'\n'+ str(count), (x,y), size=12, va='center',␣
↪ha='center')
plt.xticks([])
plt.yticks([])
plt.show()
```



- These circle plots just show the same data as the bar plots, just a different perspective

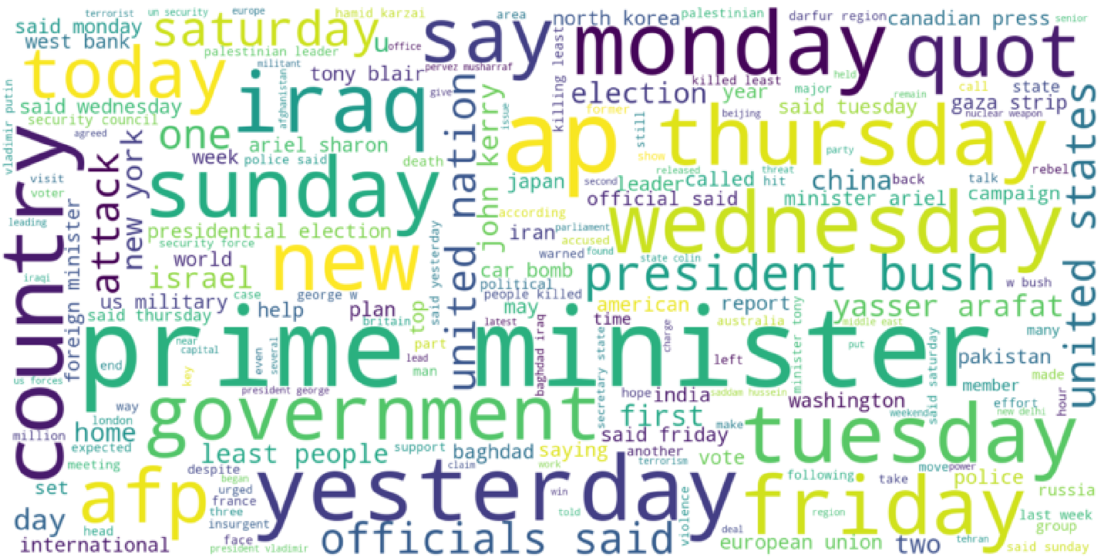
1.2.5 Word Clouds

[46]:
```
# pip install wordcloud
```

[47]:
```
#sports
#concatenate all text from the `cleaned_description` column
sports_all_text = ' '.join(sports_df_train['cleaned_description'])

#create a WordCloud object
sports_wordcloud = WordCloud(width=1600, height=800, random_state=21,␣
↪max_font_size=160, background_color='white').generate(sports_all_text)
```

```
#display the word cloud
plt.figure(figsize=(10, 5))
plt.imshow(sports_wordcloud, interpolation="bilinear")
plt.axis('off')
plt.show()
```


```
[48]: #world news
#concatenate all text from the `cleaned_description` column
world_news_all_text = ' '.join(world_news_df_train['cleaned_description'])

#create WordCloud object
world_wordcloud = WordCloud(width=1600, height=800, random_state=21,␣
↪max_font_size=160, background_color='white').generate(world_news_all_text)

#display word cloud
plt.figure(figsize=(10, 5))
plt.imshow(world_wordcloud, interpolation="bilinear")
plt.axis('off')
plt.show()
```




```
[49]: #business
#concatenate all text from the cleaned_description column
business_all_text = ' '.join(business_df_train['cleaned_description'])

#create a WordCloud object
business_wordcloud = WordCloud(width=1600, height=800, random_state=21, max_font_size=160, background_color='white').generate(business_all_text)

#display the word cloud
plt.figure(figsize=(10, 5))
plt.imshow(business_wordcloud, interpolation="bilinear")
plt.axis('off')
plt.show()
```


```
[50]: #science
      #concatenate all text from the cleaned_description column
      science_all_text = ' '.join(science_df_train['cleaned_description'])

      #create a WordCloud object
      science_wordcloud = WordCloud(width=1600, height=800, random_state=21,␣
       ↪max_font_size=160, background_color='white').generate(science_all_text)

      #display the word cloud
      plt.figure(figsize=(10, 5))
      plt.imshow(science_wordcloud, interpolation="bilinear")
      plt.axis('off')
      plt.show()
```

1.2.6 Sentiment Analysis

- Out of curiosity, we felt it might be interesting to compute the sentiment scores of the article descriptions and their titles. No real hypothesis here, just looking to see if there was any insights we could find.

[51]:
```
#download in the event package isnt installed
#nltk.download('vader_lexicon')
```

[52]:
```
#initialize SentimentIntensityAnalyzer()
sentiment = SentimentIntensityAnalyzer()

#apply the sentiment analyzer to `clean_description`
df_train['desc_sentiment_scores'] = df_train['cleaned_description'].apply(lambda description: sentiment.polarity_scores(description))
# apply the sentiment analyzer to `cleaned_title`
df_train['title_sentiment_scores'] = df_train['cleaned_title'].apply(lambda title: sentiment.polarity_scores(title))


#extract  compound sentiment score from the title sentiment scores
df_train['des_compound_score'] = df_train['desc_sentiment_scores'].apply(lambda scores: scores['compound'])
# extract  compound sentiment score from the title sentiment scores
df_train['title_compound_score'] = df_train['title_sentiment_scores'].apply(lambda scores: scores['compound'])
```

[53]:
```
df_train
```

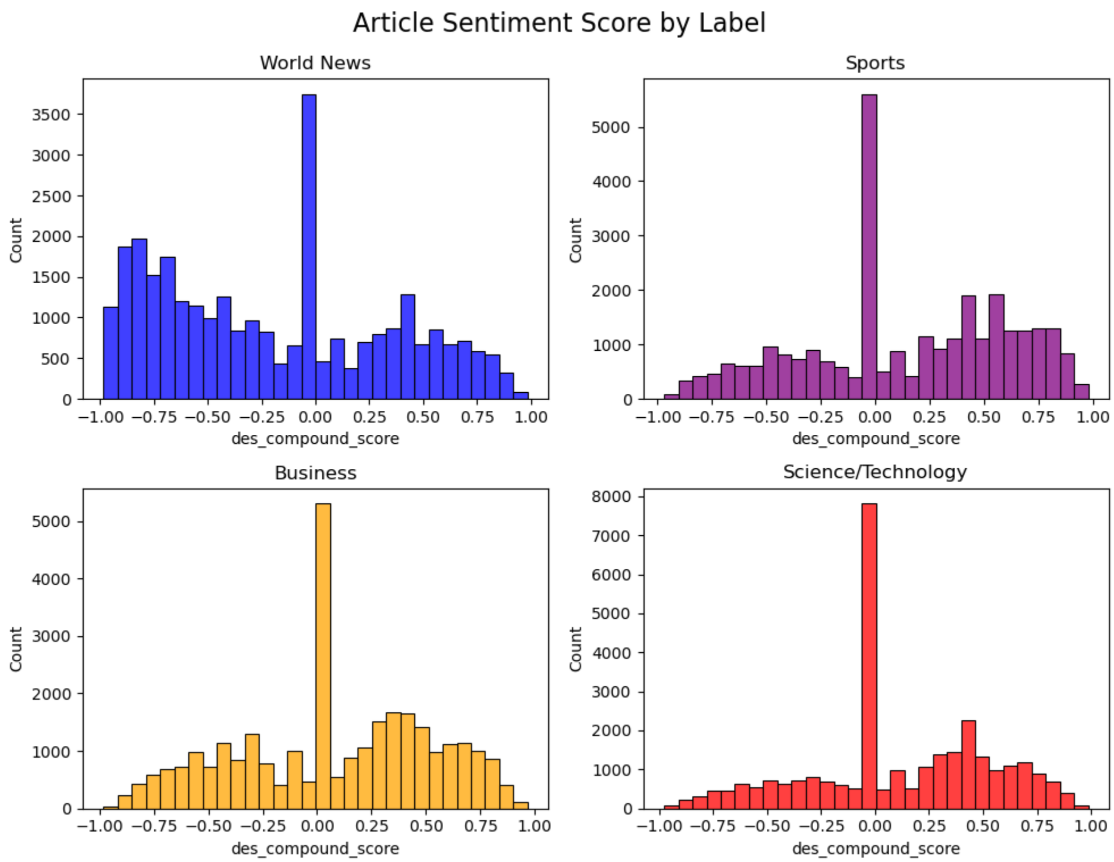
```
[53]:                                               description  label  \
0       b'AMD #39;s new dual-core Opteron chip is desi…      3
1       b'Reuters - Major League Baseball\\Monday anno…      1
2       b'President Bush #39;s  quot;revenue-neutral q…      2
3       b'Britain will run out of leading scientists u…      3
4       b'London, England (Sports Network) - England m…      1
…                                                    …    …
119995  b'Ivan Ljubicic edged No. 7 seed Joachim Johan…      1
119996  b'MANAMA: A \\$1.3 billion (BD491 million) com…      2
119997  b'And lo, the hawk begat the dove. At least th…      0
119998  b'West Palm Beach, FL (Sports Network) - Tom L…      1
119999  b'If the Federal Communications Commission has…      2

                                                    title  \
0               b'AMD Debuts Dual-Core Opteron Processor'
1                   b"Wood's Suspension Upheld (Reuters)"
2            b'Bush reform may have blue states seeing red'
3                      b"'Halt science decline in schools'"
4                                 b'Gerrard leaves practice'
…                                                    …
119995      b'Agassi, Ljubicic advance in Madrid Masters'
119996  b'\\$1.3 billion power plant will generate 3,5…
119997                              b'Last man standing'
119998          b'Report: Lehman named Ryder Cup captain'
119999  b'Got digital? By end of  #39;06, you may not …

                                      cleaned_description  \
0       amd new dualcore opteron chip designed mainly …
1       reuters major league baseballmonday announced …
2       president bush quotrevenueneutral quot tax ref…
3       britain run leading scientists unless science …
4       london england sports network england midfield…
…                                                    …
119995  ivan ljubicic edged 7 seed joachim johansson t…
119996  manama 13 billion bd491 million combined power…
119997  lo hawk begat dove least one imagines private …
119998  west palm beach fl sports network tom lehman n…
119999  federal communications commission way every am…

                                    cleaned_title  \
0          amd debuts dualcore opteron processor
1                woods suspension upheld reuters
2          bush reform may blue states seeing red
3                     halt science decline schools
4                          gerrard leaves practice
…                                            …
119995     agassi ljubicic advance madrid masters
```

```
119996  13 billion power plant generate 3500 jobs
119997                          last man standing
119998      report lehman named ryder cup captain
119999            got digital end 3906 may choice

                                    desc_sentiment_scores  \
0       {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound…
1       {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound…
2       {'neg': 0.115, 'neu': 0.78, 'pos': 0.105, 'com…
3       {'neg': 0.0, 'neu': 0.78, 'pos': 0.22, 'compou…
4       {'neg': 0.102, 'neu': 0.679, 'pos': 0.219, 'co…
…                                                     …
119995  {'neg': 0.0, 'neu': 0.868, 'pos': 0.132, 'comp…
119996  {'neg': 0.0, 'neu': 0.896, 'pos': 0.104, 'comp…
119997  {'neg': 0.0, 'neu': 0.865, 'pos': 0.135, 'comp…
119998  {'neg': 0.0, 'neu': 0.872, 'pos': 0.128, 'comp…
119999  {'neg': 0.0, 'neu': 0.876, 'pos': 0.124, 'comp…

                                   title_sentiment_scores  des_compound_score  \
0       {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound…              0.0000
1       {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound…              0.0000
2       {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound…             -0.0772
3       {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound…              0.4767
4       {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound…              0.4767
…                                                     …                  …
119995  {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound…              0.2263
119996  {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound…              0.2732
119997  {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound…              0.5574
119998  {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound…              0.4215
119999  {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound…              0.4019

        title_compound_score
0                        0.0
1                        0.0
2                        0.0
3                        0.0
4                        0.0
…                      …
119995                   0.0
119996                   0.0
119997                   0.0
119998                   0.0
119999                   0.0

[120000 rows x 9 columns]
```

Sentiment Analysis - Plots

[54]:

```
#setting up subplots
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(10, 8))

#plot histograms for each label
sns.histplot(df_train[df_train['label']==0]['des_compound_score'], bins=30,␣
 ↪color='blue', ax=axes[0, 0])
axes[0, 0].set_title('World News')

sns.histplot(df_train[df_train['label']==1]['des_compound_score'], bins=30,␣
 ↪color='purple', ax=axes[0, 1])
axes[0, 1].set_title('Sports')

sns.histplot(df_train[df_train['label']==2]['des_compound_score'], bins=30,␣
 ↪color='orange', ax=axes[1, 0])
axes[1, 0].set_title('Business')

sns.histplot(df_train[df_train['label']==3]['des_compound_score'], bins=30,␣
 ↪color='red', ax=axes[1, 1])
axes[1, 1].set_title('Science/Technology')

#layout
plt.tight_layout()
plt.tight_layout(rect=[0, 0.03, 1, 0.95])

#all plots title
plt.suptitle('Article Sentiment Score by Label', fontsize=16)

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



The sentiment analysis from the nltk library computes three scores for negativity, neutral, and positivity. These three scores are then calculated together to get the compound score.

The above plots show the compound scores for all four article types. We can see that the World News articles had a lower amount of neutral articles and a higher number of articles that were negative than the other categories.

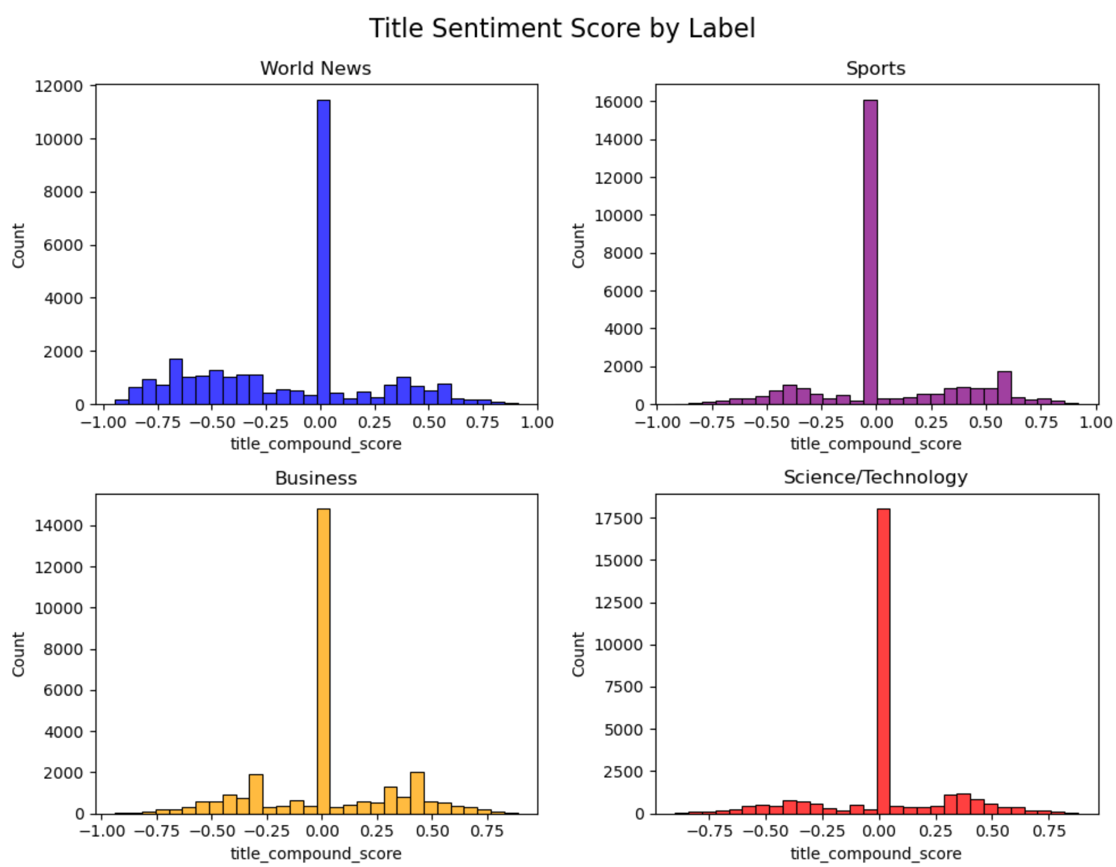
Sports articles had more positive articles than negative ones. This trend is mostly similar for the Business article category.

Science and technology had significantly more neutral articles than the other categories.

Not much can really be gleaned from this.

[55]:
```
#subplots
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(10, 8))

#plot histograms for each label
sns.histplot(df_train[df_train['label']==0]['title_compound_score'], bins=30,␣
 ↪color='blue', ax=axes[0, 0])#, kde=True)
axes[0, 0].set_title('World News')
```

```
sns.histplot(df_train[df_train['label']==1]['title_compound_score'], bins=30,␣
↪color='purple', ax=axes[0, 1])#, kde=True)
axes[0, 1].set_title('Sports')

sns.histplot(df_train[df_train['label']==2]['title_compound_score'], bins=30,␣
↪color='orange', ax=axes[1, 0])#, kde=True)
axes[1, 0].set_title('Business')

sns.histplot(df_train[df_train['label']==3]['title_compound_score'], bins=30,␣
↪color='red', ax=axes[1, 1])#, kde=True)
axes[1, 1].set_title('Science/Technology')

#layout
plt.tight_layout()
plt.tight_layout(rect=[0, 0.03, 1, 0.95])

#all plots title
plt.suptitle('Title Sentiment Score by Label', fontsize=16)

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

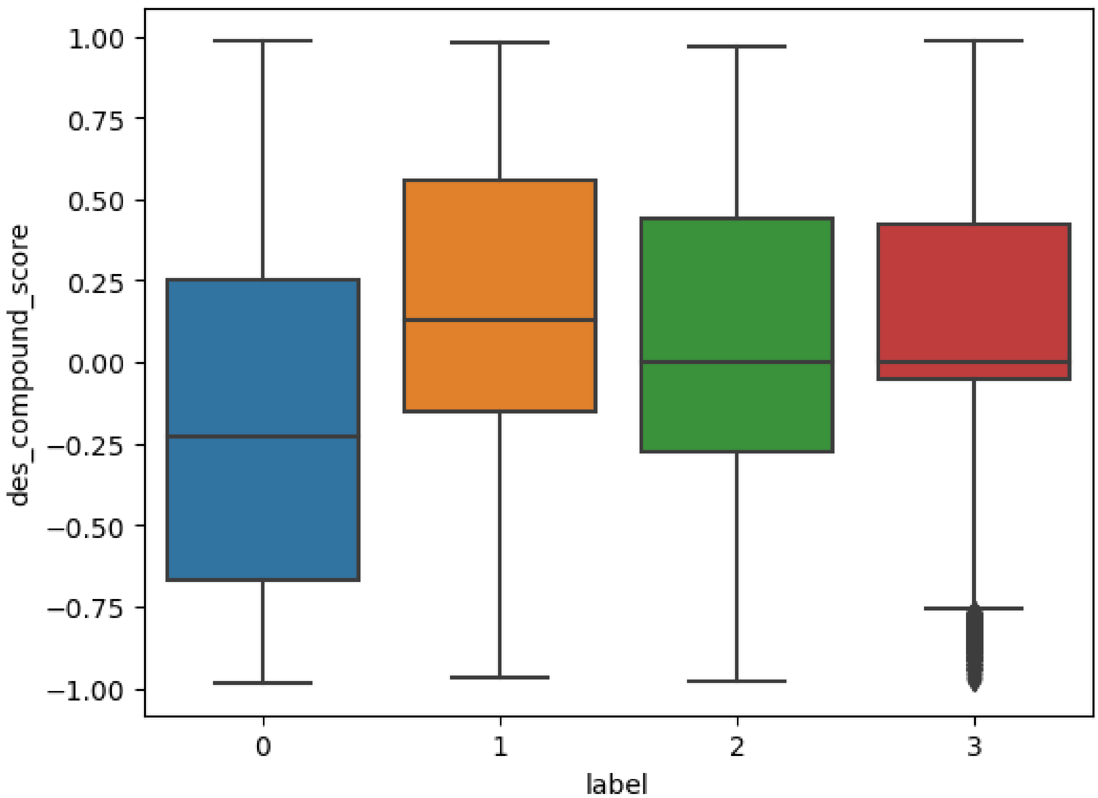


Looking at the sentiment of just the titles, the World News titles followed the trend that the descriptions with more negative scores than positives, excluding the neutral ones.

The other article types mainly had neutral titles. Again, not much really can be learned from this.

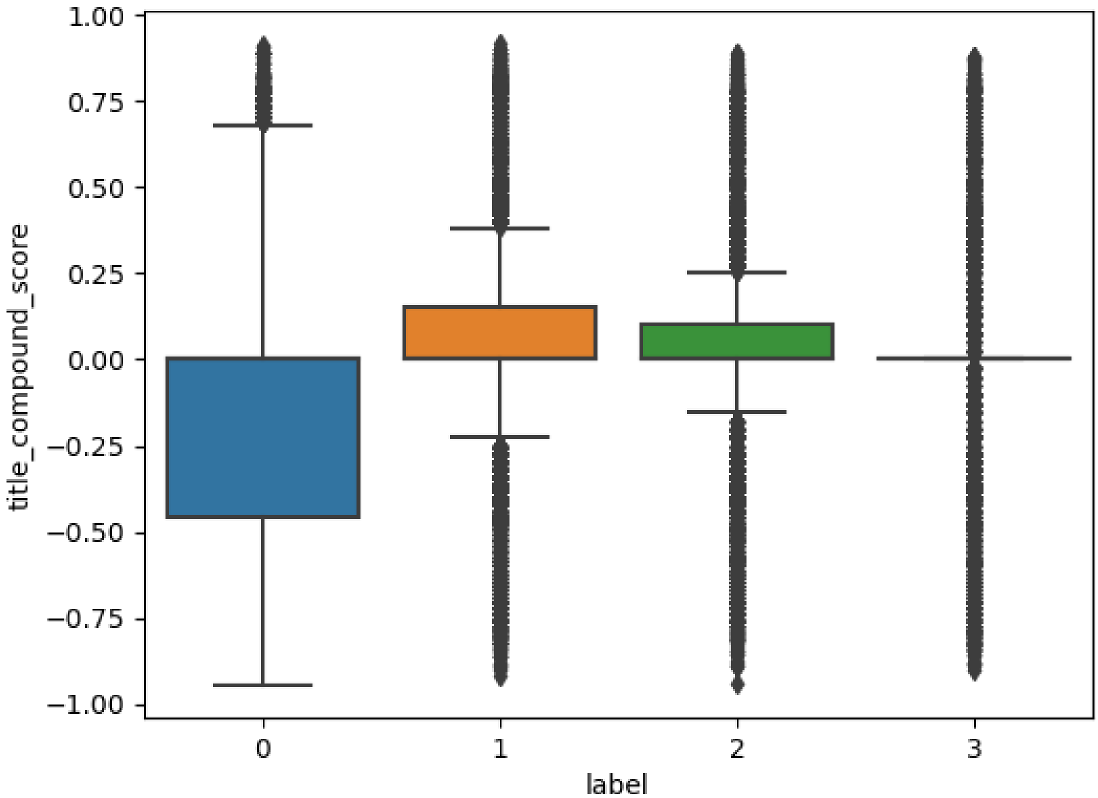
[56]:
```
#boxplot of the description sentiment score by labels
sns.boxplot(x='label', y='des_compound_score', data=df_train)
```

[56]: <Axes: xlabel='label', ylabel='des_compound_score'>



[57]:
```
#boxplot of the title sentiment score by labels
sns.boxplot(x='label', y='title_compound_score', data=df_train)
```

[57]: <Axes: xlabel='label', ylabel='title_compound_score'>



1.2.7 N-grams

[58]:
```
#function to find number of n-grams
def ngrams(tokens, n, top=10):
    #looping through tokens to create a list of n-grams
    n_grams = [' '.join(tokens[i:i+n]) for i in range(len(tokens)-n+1)]

    #counts the n_grams to find most frequent
    n_gram_counts = Counter(n_grams)

    #limits the to the designated top number of n_grams
    most_common_ngrams = n_gram_counts.most_common(top)

    return most_common_ngrams
```

[59]:
```
#function for n_gram plot
def plot_n_grams(df, n="bi?", title="ENTER"):
    plt.figure(figsize=(10, 6))
    plt.barh(df['n_gram'], df['frequency'], color='skyblue')
    plt.title(f'Top {title} {n}-grams')
    plt.xlabel(f'{n}_gram')
```

```
    plt.ylabel('frequency')
    plt.show()
```

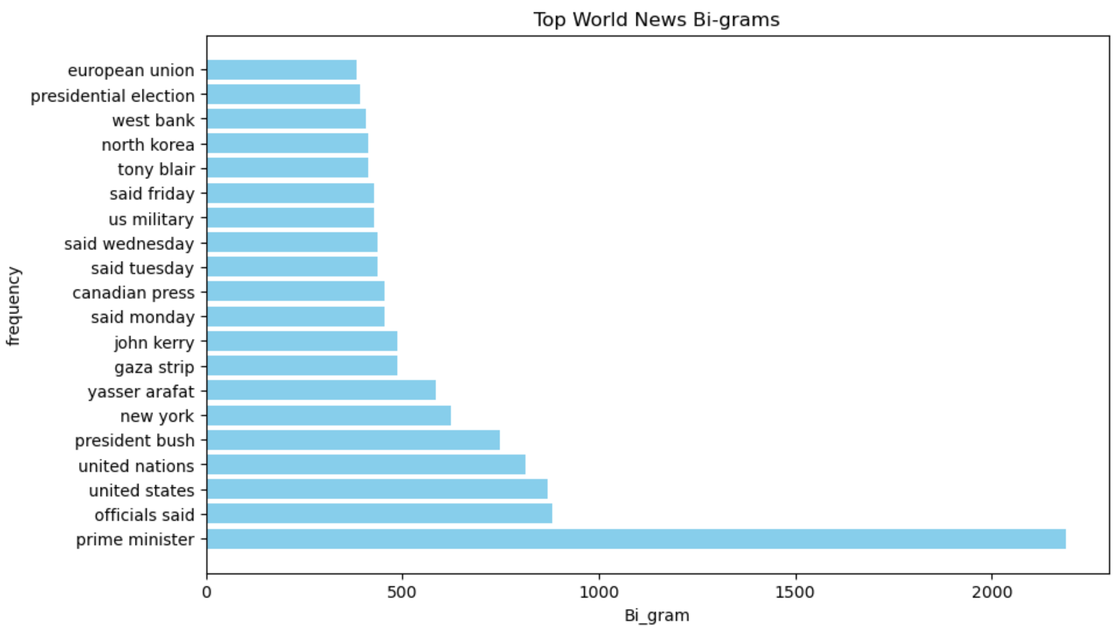
world news n-grams

[60]:
```
#tokenizing all words
world_news_tokens = word_tokenize(world_news_all_text)

#creating world news bi-gram df
world_bi_grams_df = pd.DataFrame(ngrams(world_news_tokens, n=2, top=20),
 ↪columns=['n_gram', 'frequency'])

world_bi_grams_df
```

[60]:

	n_gram	frequency
0	prime minister	2188
1	officials said	881
2	united states	871
3	united nations	813
4	president bush	747
5	new york	625
6	yasser arafat	586
7	gaza strip	488
8	john kerry	487
9	said monday	456
10	canadian press	454
11	said tuesday	437
12	said wednesday	437
13	us military	429
14	said friday	427
15	tony blair	414
16	north korea	412
17	west bank	408
18	presidential election	391
19	european union	384

[61]:
```
#plotting world news bi-grams
plot_n_grams(world_bi_grams_df, n='Bi',title="World News")
```

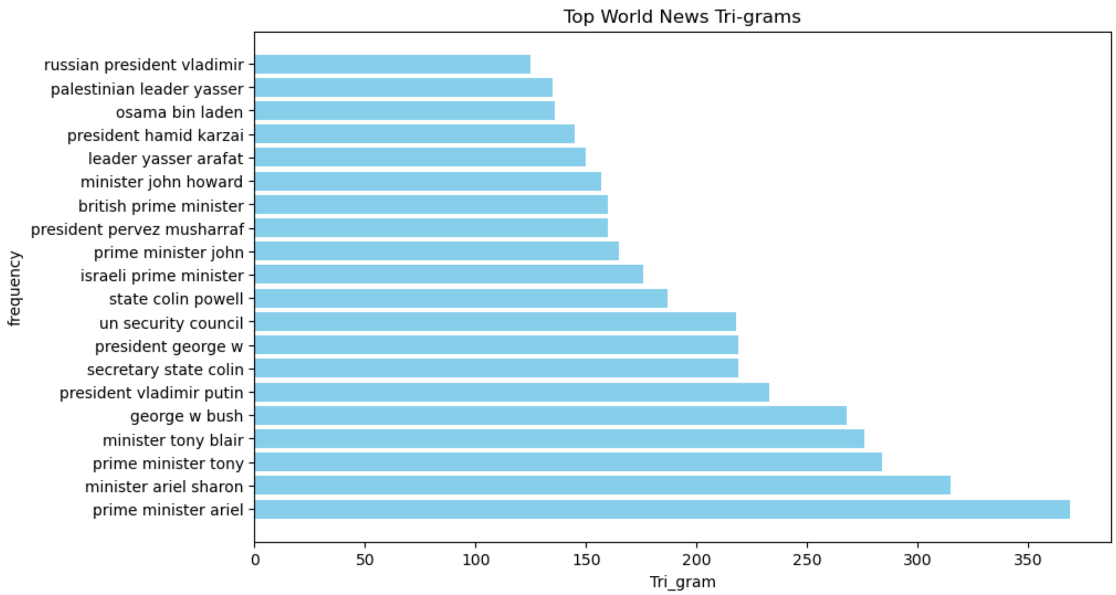


[62]:
```python
world_tri_grams_df = pd.DataFrame(ngrams(world_news_tokens, n=3, top=20),
    columns=['n_gram', 'frequency'])

world_tri_grams_df
```

[62]:

	n_gram	frequency
0	prime minister ariel	369
1	minister ariel sharon	315
2	prime minister tony	284
3	minister tony blair	276
4	george w bush	268
5	president vladimir putin	233
6	secretary state colin	219
7	president george w	219
8	un security council	218
9	state colin powell	187
10	israeli prime minister	176
11	prime minister john	165
12	president pervez musharraf	160
13	british prime minister	160
14	minister john howard	157
15	leader yasser arafat	150
16	president hamid karzai	145
17	osama bin laden	136
18	palestinian leader yasser	135
19	russian president vladimir	125

[63]:
```
plot_n_grams(world_tri_grams_df, n='Tri', title="World News")
```



sports n-grams

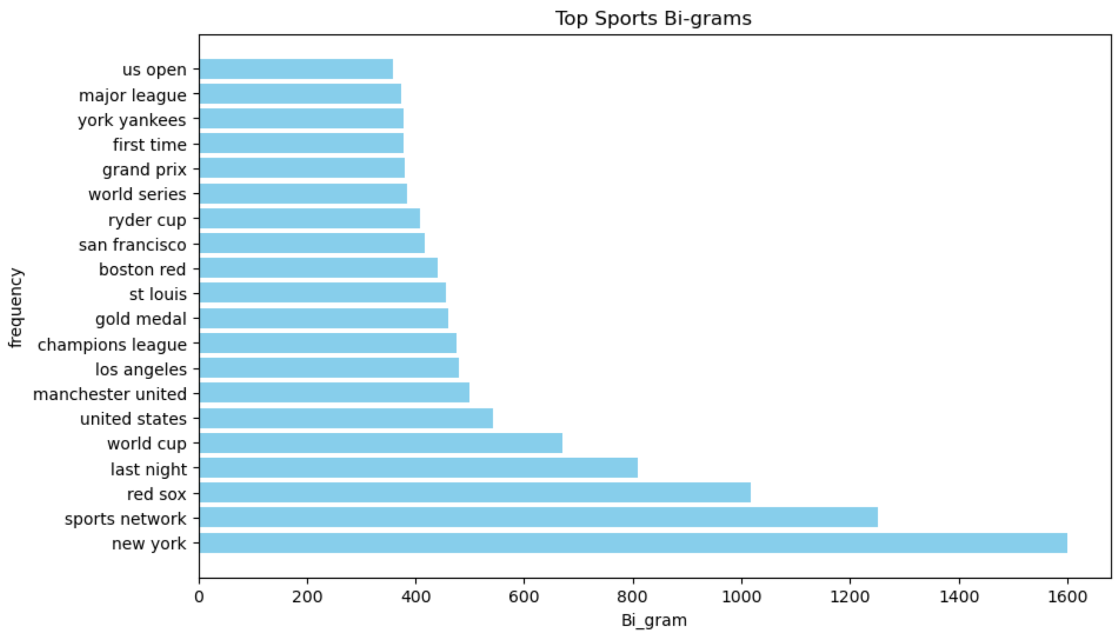
[64]:
```
#tokenizing all words in sports articles
sports_tokens = word_tokenize(sports_all_text)

#bi-grams for sports articles
sports_bi_grams_df = pd.DataFrame(ngrams(sports_tokens, n=2, top=20),␣
 ↪columns=['n_gram', 'frequency'])

sports_bi_grams_df
```

[64]:

	n_gram	frequency
0	new york	1599
1	sports network	1250
2	red sox	1016
3	last night	810
4	world cup	671
5	united states	543
6	manchester united	499
7	los angeles	479
8	champions league	475
9	gold medal	460
10	st louis	457
11	boston red	441
12	san francisco	416
13	ryder cup	408

```
14       world series        384
15         grand prix        380
16         first time        379
17       york yankees        377
18       major league        373
19            us open        359
```

[65]:
```python
plot_n_grams(sports_bi_grams_df, n='Bi', title='Sports')
```



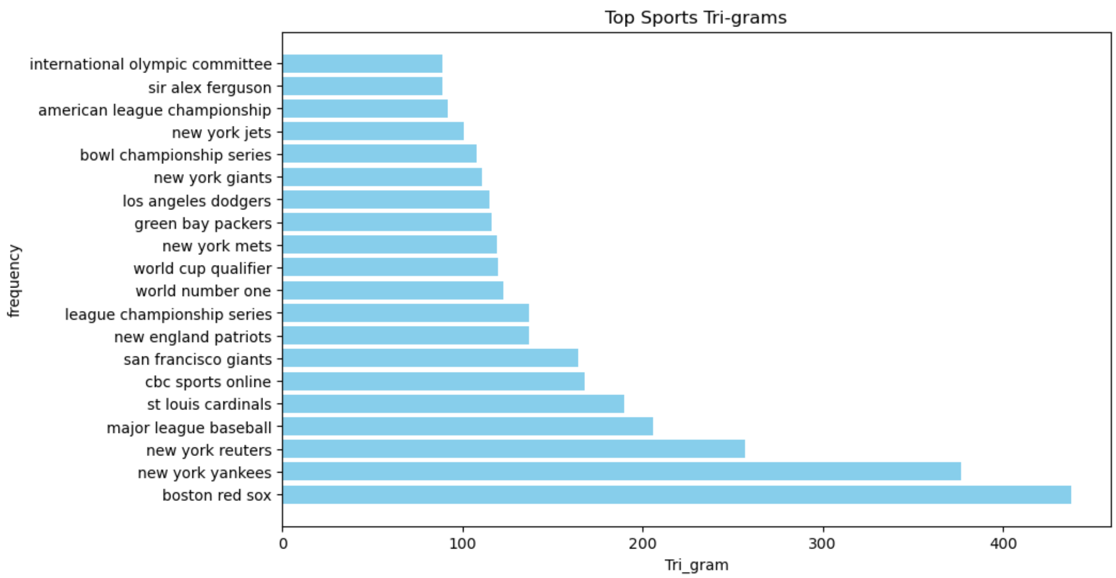
[66]:
```python
#tri-grams for sports articles
sports_tri_grams_df = pd.DataFrame(ngrams(sports_tokens, n=3, top=20),␣
↪columns=['n_gram', 'frequency'])

sports_tri_grams_df
```

[66]:

	n_gram	frequency
0	boston red sox	438
1	new york yankees	377
2	new york reuters	257
3	major league baseball	206
4	st louis cardinals	190
5	cbc sports online	168
6	san francisco giants	164
7	new england patriots	137
8	league championship series	137
9	world number one	123

```
10              world cup qualifier        120
11                   new york mets         119
12                green bay packers        116
13              los angeles dodgers        115
14                 new york giants         111
15          bowl championship series       108
16                   new york jets         101
17      american league championship        92
18                sir alex ferguson         89
19   international olympic committee        89
```

[67]:
```python
plot_n_grams(sports_tri_grams_df, n='Tri', title='Sports')
```



business n-grams

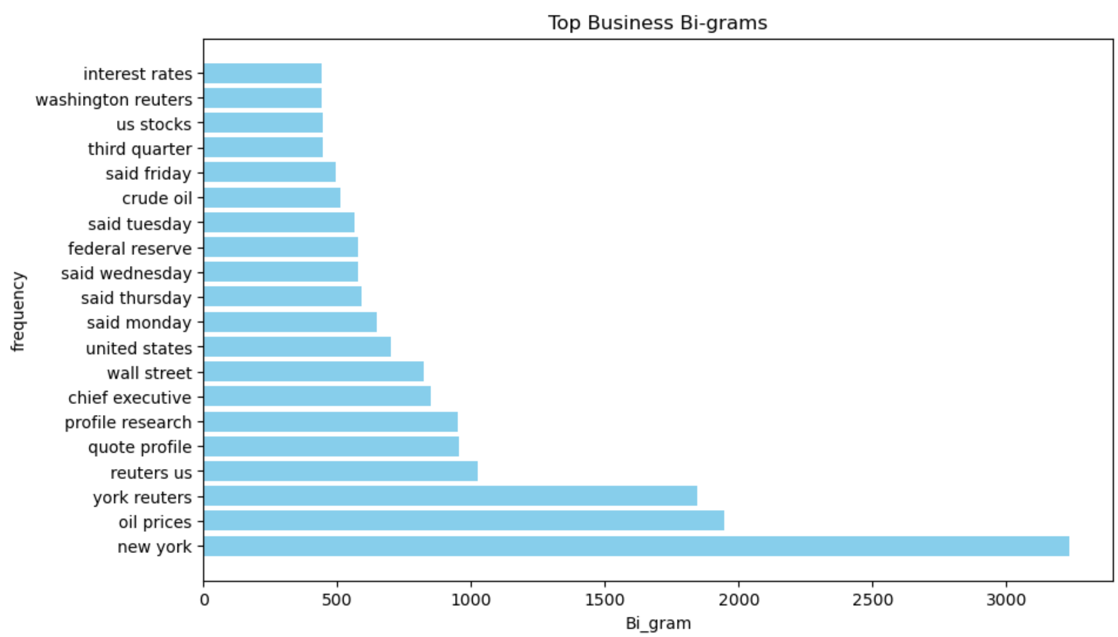
[68]:
```python
#tokenizing all words in sports articles
business_tokens = word_tokenize(business_all_text)

#bi-grams for sports articles
business_bi_grams_df = pd.DataFrame(ngrams(business_tokens, n=2, top=20),
 ↪columns=['n_gram', 'frequency'])

business_bi_grams_df
```

[68]:

	n_gram	frequency
0	new york	3237
1	oil prices	1947
2	york reuters	1843

```
3          reuters us        1026
4       quote profile         954
5    profile research         952
6     chief executive         847
7         wall street         823
8       united states         698
9         said monday         648
10      said thursday         590
11     said wednesday         579
12    federal reserve         575
13       said tuesday         566
14          crude oil         512
15        said friday         492
16      third quarter         446
17          us stocks         444
18 washington reuters         443
19     interest rates         442
```

[69]:
```python
plot_n_grams(business_bi_grams_df, n='Bi', title='Business')
```

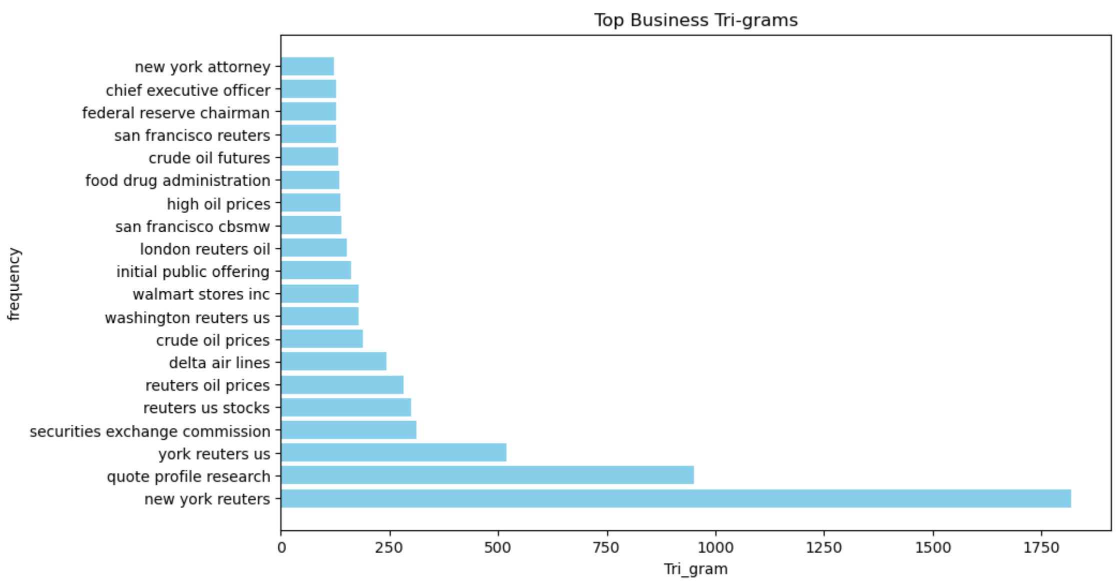


[70]:
```python
#tri-grams for sports articles
business_tri_grams_df = pd.DataFrame(ngrams(business_tokens, n=3, top=20),␣
↪columns=['n_gram', 'frequency'])

business_tri_grams_df
```

[70]:

	n_gram	frequency
0	new york reuters	1820
1	quote profile research	952
2	york reuters us	520
3	securities exchange commission	313
4	reuters us stocks	299
5	reuters oil prices	282
6	delta air lines	242
7	crude oil prices	188
8	washington reuters us	180
9	walmart stores inc	178
10	initial public offering	161
11	london reuters oil	152
12	san francisco cbsmw	140
13	high oil prices	138
14	food drug administration	134
15	crude oil futures	131
16	san francisco reuters	128
17	federal reserve chairman	126
18	chief executive officer	126
19	new york attorney	123

[71]:
```
plot_n_grams(business_tri_grams_df, n='Tri', title='Business')
```



Science n-grams

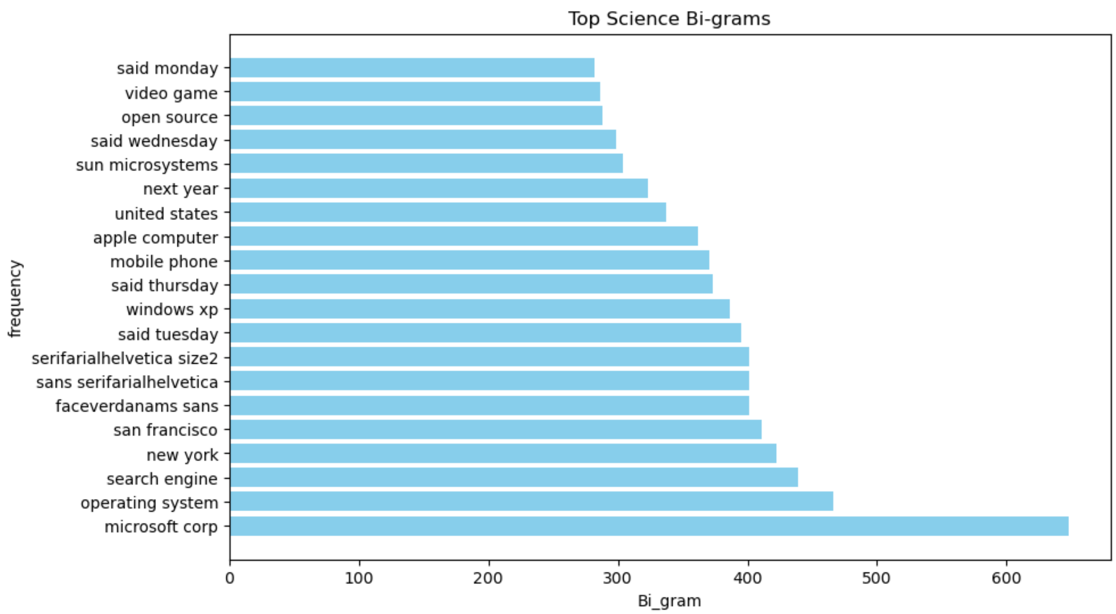
[72]:
```
#tokenizing all words in sports articles
science_tokens = word_tokenize(science_all_text)
```

```
#bi-grams for sports articles
science_bi_grams_df = pd.DataFrame(ngrams(science_tokens, n=2, top=20),␣
↪columns=['n_gram', 'frequency'])

science_bi_grams_df
```

[72]:

	n_gram	frequency
0	microsoft corp	648
1	operating system	466
2	search engine	439
3	new york	422
4	san francisco	411
5	faceverdanams sans	401
6	sans serifarialhelvetica	401
7	serifarialhelvetica size2	401
8	said tuesday	395
9	windows xp	386
10	said thursday	373
11	mobile phone	371
12	apple computer	362
13	united states	337
14	next year	323
15	sun microsystems	304
16	said wednesday	299
17	open source	288
18	video game	286
19	said monday	282

[73]:
```
plot_n_grams(science_bi_grams_df, n='Bi', title='Science')
```

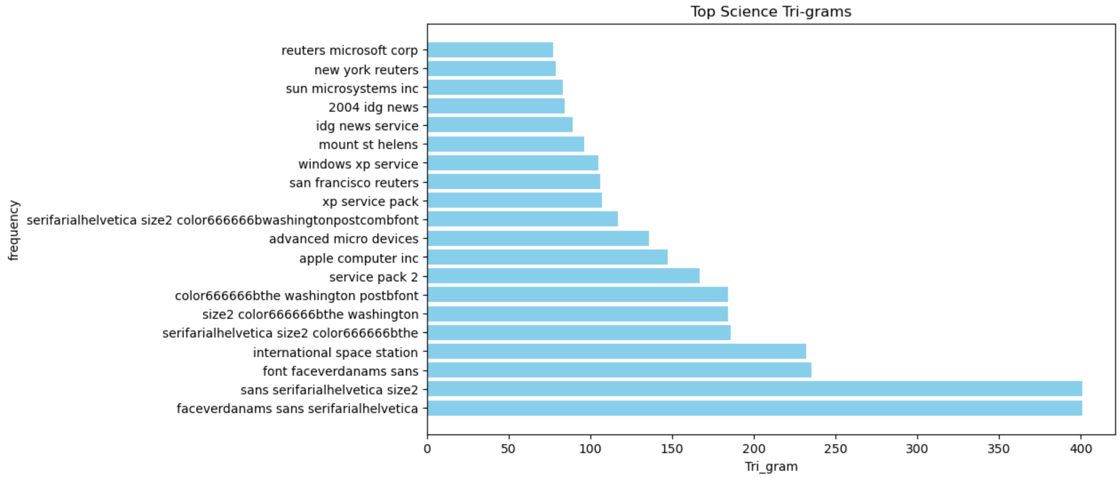


[74]:
```python
#tri-grams for sports articles
science_tri_grams_df = pd.DataFrame(ngrams(science_tokens, n=3, top=20),
 ↪columns=['n_gram', 'frequency'])

science_tri_grams_df
```

[74]:

	n_gram	frequency
0	faceverdanams sans serifarialhelvetica	401
1	sans serifarialhelvetica size2	401
2	font faceverdanams sans	235
3	international space station	232
4	serifarialhelvetica size2 color666666bthe	186
5	size2 color666666bthe washington	184
6	color666666bthe washington postbfont	184
7	service pack 2	167
8	apple computer inc	147
9	advanced micro devices	136
10	serifarialhelvetica size2 color666666bwashingt…	117
11	xp service pack	107
12	san francisco reuters	106
13	windows xp service	105
14	mount st helens	96
15	idg news service	89
16	2004 idg news	84
17	sun microsystems inc	83
18	new york reuters	79
19	reuters microsoft corp	77

[75]:
```
plot_n_grams(science_tri_grams_df, n='Tri', title='Science')
```



- Looking at the n-grams for the article types, we can see that there is more division between them. The terms are in line with what you would expect for each type of article. This leads to the positive idea that the models will have success in classifying the types of articles.

1.3 Baseline Models

Re-cleaning datasets to remove all non letters

[76]:
```
#function to convert a raw text from loaded dataset to string

def clean_words_only_letters(raw_description):

    #remove HTML
    description_text = BeautifulSoup(raw_description).get_text()

    #remove non-letters
    letters_only = re.sub(r'[^a-zA-Z]', ' ', description_text)

    #removing html artifact 39s from when apostrophe errored
    final_clean = re.sub(r'39s', '', letters_only)

    #convert to lower case, split into individual words.
    words = final_clean.lower().split()

    #setting stop words
    stops = set(stopwords.words('english'))

    #remove stop words.
    meaningful_words = [w for w in words if w not in stops]
```

```
    #join the words into one string, return result.
    return(" ".join(meaningful_words))
```

[77]:
```
#data import from provided code
import tensorflow_datasets as tfds
train_data, test_data = tfds.load(
  'ag_news_subset',
  split = ['train', 'test'],
  batch_size = -1
)
df_train_2 = pd.DataFrame(train_data)
df_test_2 = pd.DataFrame(test_data)
```

[78]:
```
#applying function over description column creating new column
df_train_2['cleaned_description'] = df_train_2['description'].
 ↪apply(clean_words_only_letters)
df_train_2['cleaned_title'] = df_train_2['title'].
 ↪apply(clean_words_only_letters)
```

```
/var/folders/9l/8vvnk63j2j9f_hg8yf6z57v80000gn/T/ipykernel_5904/3208799350.py:6:
MarkupResemblesLocatorWarning: The input looks more like a filename than markup.
You may want to open this file and pass the filehandle into Beautiful Soup.
  description_text = BeautifulSoup(raw_description).get_text()
/var/folders/9l/8vvnk63j2j9f_hg8yf6z57v80000gn/T/ipykernel_5904/3208799350.py:6:
MarkupResemblesLocatorWarning: The input looks more like a filename than markup.
You may want to open this file and pass the filehandle into Beautiful Soup.
  description_text = BeautifulSoup(raw_description).get_text()
```

creating training set with all labels

[79]:
```
#labeling all non-sports articles as 0
df_train_2['label'] = df_train_2['label'].map(lambda x: 1 if x == 1 else 0)
```

[80]:
```
#creating y_train target variable
y_train = df_train_2['label']
```

Cleaning Test Set

- test set cleaned the same way the training set was

[81]:
```
#applying function over description column creating new column
df_test_2['cleaned_description'] = df_test_2['description'].
 ↪apply(clean_words_only_letters)
df_test_2['cleaned_title'] = df_test_2['title'].apply(clean_words_only_letters)
```

```
/var/folders/9l/8vvnk63j2j9f_hg8yf6z57v80000gn/T/ipykernel_5904/3208799350.py:6:
MarkupResemblesLocatorWarning: The input looks more like a filename than markup.
You may want to open this file and pass the filehandle into Beautiful Soup.
  description_text = BeautifulSoup(raw_description).get_text()
```

```
/var/folders/9l/8vvnk63j2j9f_hg8yf6z57v80000gn/T/ipykernel_5904/3208799350.py:6:
MarkupResemblesLocatorWarning: The input looks more like a filename than markup.
You may want to open this file and pass the filehandle into Beautiful Soup.
  description_text = BeautifulSoup(raw_description).get_text()
```

1.3.1 Creating test set from all labels

[82]:
```
df_test_2['label'] = df_test_2['label'].map(lambda x: 1 if x == 1 else 0)

#checking to see the proportion of the sports label
sports_article_porportion = len(df_test_2[df_test_2['label']==1])/len(df_test)

print(f'Proportion of sports articles in dataset: {sports_article_porportion}')
```

```
Proportion of sports articles in dataset: 0.25
```

[83]:
```
y_test = df_test_2['label']
```

Logistic Regression

ngram - 1

[84]:
```
start_time = time.time()

#creating tfidf from data
tfidf_1 = TfidfVectorizer(max_features=10000,
                        ngram_range=(1,1),
                        stop_words='english',
                        max_df = 1.0)

#fit and trasnforming vectorizer to training data
X_train_1 = tfidf_1.fit_transform(df_train_2['cleaned_description'])

#applying transform to test data
X_test_1 = tfidf_1.transform(df_test_2['cleaned_description'])

end_time = time.time()

elapsed_time = end_time - start_time
print(f"Elapsed time: {elapsed_time:.4f} seconds")
```

```
Elapsed time: 0.9268 seconds
```

- looking at the F1 score we can see a generally good model was fit from our data. The fact that the model was able to obtain an f1 score with an imbalanced data set is great for a simple model.

[85]:
```
start_time = time.time()

#fitting logistic regression model with l1 regularization
```

```
lr_1_tfidf = LogisticRegression(penalty='l1', solver='liblinear')

#fitting model
lr_1_tfidf.fit(X_train_1, y_train)

end_time = time.time()

elapsed_time = end_time - start_time
print(f"Elapsed time: {elapsed_time:.4f} seconds")
```

```
Elapsed time: 0.3222 seconds
```

[86]:
```
start_time = time.time()

#predictions
lr_1_tfidf_preds = lr_1_tfidf.predict(X_test_1)

end_time = time.time()

elapsed_time = end_time - start_time
print(f"Elapsed time: {elapsed_time:.4f} seconds")
```

```
Elapsed time: 0.0007 seconds
```

[87]:
```
#classification report to see many metrics
lr_1_tfidf_classification_rep = classification_report(y_test, lr_1_tfidf_preds)

print("Logisti Regresion Classification Report:")
print(lr_1_tfidf_classification_rep)
```

```
Logisti Regresion Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.99      0.98      5700
           1       0.96      0.94      0.95      1900

    accuracy                           0.98      7600
   macro avg       0.97      0.96      0.97      7600
weighted avg       0.98      0.98      0.98      7600
```

[88]:
```
f1_score(y_test, lr_1_tfidf_preds)
```

[88]: 0.9511677282377919

[89]:
```
#function to find top coefficients
def model_coef(model, tfidf, n=25):
    #finding model coefficients
    coefficients = model.coef_
```

```
    #getting feature names
    feature_names = np.array(tfidf.get_feature_names_out())

    # Get indices of top n features
    top_feature_indices = coefficients.argsort()[0, -n:][::-1]

    #top features from pca reduced tfidf
    top_coeff_words = feature_names[top_feature_indices]

    print(top_coeff_words)
```

[90]:
```
#printing top 50 model coefficients
model_coef(lr_1_tfidf, tfidf_1, n=50)
```

```
['cup' 'coach' 'nascar' 'sports' 'nhl' 'hendrick' 'cricket' 'quarterback'
 'kobe' 'stadium' 'sox' 'manchester' 'notre' 'formula' 'nba' 'football'
 'auburn' 'teams' 'olympics' 'rugby' 'doping' 'pitcher' 'baseball'
 'league' 'prix' 'olympic' 'cleveland' 'mets' 'team' 'nfl' 'wenger'
 'season' 'turin' 'redskins' 'ncaa' 'pacers' 'striker' 'manager' 'coaches'
 'bowl' 'basketball' 'champion' 'tennis' 'defensive' 'club' 'coaching'
 'championship' 'caminiti' 'players' 'boxing']
```

[91]:
```
#function to show misclassified articles
def classification_examples(y_test, y_pred, X_test):

    #finding where model misclassified on testing set
    misclassified_indicies = (y_test != y_pred)

    #creating subset for misclassified articles
    misclass_examples = X_test[misclassified_indicies]

    #creating labels for misclassified answers
    answer_label = y_test[misclassified_indicies]

    #creating label for what was predicted
    predicted_label = y_pred[misclassified_indicies]

    #creating subset of mislabled classes
    shortened_misclass_examples = misclass_examples[:5]

    print(f'Number of misclassifications: {len(misclass_examples)}\n')

    #loop for print out first 5 misclassified article
    #print the predictions and answer lables
    for i in range(len(shortened_misclass_examples)):
        print(f'{i+1} - {shortened_misclass_examples.iloc[i]}')
```

```
        print(f'Real Label: {answer_label.iloc[i]}, Predicted Label:␣
↪{predicted_label[i]}')
        print('\n')
```

[92]:
```
classification_examples(y_test, lr_1_tfidf_preds,␣
↪df_test_2['cleaned_description'])
```

```
Number of misclassifications: 184

1 - sebastian sainsbury warned leeds united chiefs today face stark choice
accepting million bid selling elland road
Real Label: 1, Predicted Label: 0


2 - probably heard one toughest endurance sports around deca ironman km swimming
immediately followed km bicycle ride km run currently world record stands hours
held german housewife nobody else ever finished course hours
Real Label: 0, Predicted Label: 1


3 - three banks go high court london seeking ruling could lead bernie ecclestone
losing control formula one racing
Real Label: 0, Predicted Label: 1


4 - everton chairman bill kenwright plans russian revolution goodison park may
thawed cold war director paul gregg
Real Label: 1, Predicted Label: 0


5 - san diego wake another downgrading san diego credit rating mayor dick murphy
today reassured public city fiscally sound
Real Label: 0, Predicted Label: 1
```

ngram - 2

[93]:
```
start_time = time.time()

#creating tfidf from data
tfidf_2 = TfidfVectorizer(max_features=10000,
                          ngram_range=(1,2),
                          stop_words='english',
                          max_df = 1.0)
```

```
#fit and trasnforming vectorizer to training data
X_train_2 = tfidf_2.fit_transform(df_train_2['cleaned_description'])

#applying transform to test data
X_test_2 = tfidf_2.transform(df_test_2['cleaned_description'])

end_time = time.time()

elapsed_time = end_time - start_time
print(f"Elapsed time: {elapsed_time:.4f} seconds")
```

```
Elapsed time: 3.5064 seconds
```

pca transformation

[95]:
```
start_time = time.time()

#instantiating logisitic regression model
lr_2_tfidf = LogisticRegression(penalty='l1', solver='liblinear')

#fitting model
lr_2_tfidf.fit(X_train_2, y_train)

end_time = time.time()

elapsed_time = end_time - start_time
print(f"Elapsed time: {elapsed_time:.4f} seconds")
```

```
Elapsed time: 0.3777 seconds
```

[96]:
```
start_time = time.time()

#preds
lr_2_tfidf_preds = lr_2_tfidf.predict(X_test_2)

end_time = time.time()

elapsed_time = end_time - start_time
print(f"Elapsed time: {elapsed_time:.4f} seconds")
```

```
Elapsed time: 0.0021 seconds
```

[97]:
```
lr_2_tfidf_classification_rep = classification_report(y_test, lr_2_tfidf_preds)

print("Logisti Regresion Classification Report:")
print(lr_2_tfidf_classification_rep)
```

```
Logisti Regresion Classification Report:
              precision    recall  f1-score   support
```

```
              0       0.98      0.99      0.98      5700
              1       0.96      0.94      0.95      1900

       accuracy                           0.98      7600
      macro avg       0.97      0.97      0.97      7600
   weighted avg       0.98      0.98      0.98      7600
```

[98]:
```python
round(f1_score(y_test, lr_2_tfidf_preds),4)
```

[98]:
```
0.9517
```

[99]:
```python
model_coef(lr_2_tfidf, tfidf_2, n=50)
```

```
['cup' 'coach' 'nascar' 'cricket' 'nhl' 'hendrick' 'kobe' 'quarterback'
 'sports' 'stadium' 'basketball' 'sox' 'league' 'nba' 'formula' 'football'
 'prix' 'auburn' 'team' 'pitcher' 'olympics' 'teams' 'baseball'
 'championship' 'pacers' 'cleveland' 'wenger' 'mets' 'doping' 'season'
 'striker' 'rugby' 'olympic' 'nfl' 'bowl' 'turin' 'ncaa' 'manager'
 'redskins' 'defensive' 'bryant' 'coaches' 'patriots' 'champion' 'club'
 'caminiti' 'athletic' 'ticker' 'tennis' 'players']
```

[100]:
```python
classification_examples(y_test, lr_2_tfidf_preds,␣
 ↪df_test_2['cleaned_description'])
```

```
Number of misclassifications: 182

1 - sebastian sainsbury warned leeds united chiefs today face stark choice
accepting million bid selling elland road
Real Label: 1, Predicted Label: 0


2 - probably heard one toughest endurance sports around deca ironman km swimming
immediately followed km bicycle ride km run currently world record stands hours
held german housewife nobody else ever finished course hours
Real Label: 0, Predicted Label: 1


3 - three banks go high court london seeking ruling could lead bernie ecclestone
losing control formula one racing
Real Label: 0, Predicted Label: 1


4 - everton chairman bill kenwright plans russian revolution goodison park may
thawed cold war director paul gregg
Real Label: 1, Predicted Label: 0
```

```
5 - big fish like richie sexson still looking work prizes like tim hudson
dangled market orioles remain hopeful bag big catch
Real Label: 1, Predicted Label: 0
```

- There was a very slight improvement on the 1-ngram model, just by 1 point on the F1 score

logistic regression - balanced class weight Because we have unbalanced classes, sports articles is .25% of the entire dataset, it would be a good idea to see how the model reacts when the classes weights are balanced

[101]:
```
start_time = time.time()

#instantiating logisitic regression model
lr_3 = LogisticRegression(penalty='l1', solver='liblinear',␣
↪class_weight='balanced')

#fitting model
lr_3.fit(X_train_2, y_train)

end_time = time.time()

elapsed_time = end_time - start_time
print(f"Elapsed time: {elapsed_time:.4f} seconds")
```

```
Elapsed time: 0.3794 seconds
```

[102]:
```
start_time = time.time()

#preds
lr_3_preds = lr_3.predict(X_test_2)

end_time = time.time()

elapsed_time = end_time - start_time
print(f"Elapsed time: {elapsed_time:.4f} seconds")
```

```
Elapsed time: 0.0027 seconds
```

[103]:
```
#creating classification report
lr_3_classification_rep = classification_report(y_test, lr_3_preds)

print("Logisti Regresion Classification Report:")
print(lr_3_classification_rep)
```

```
Logisti Regresion Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.98      0.98      5700
```

```
           1       0.94      0.97      0.96      1900

    accuracy                           0.98      7600
   macro avg       0.97      0.98      0.97      7600
weighted avg       0.98      0.98      0.98      7600
```

[104]:
```
round(f1_score(y_test, lr_3_preds),4)
```

[104]:
```
0.9555
```

[105]:
```
#top 50 model coeffients
model_coef(lr_3, tfidf_2, n=50)
```

```
['cup' 'coach' 'nascar' 'cricket' 'sports' 'nhl' 'hendrick' 'stadium'
 'quarterback' 'sox' 'formula' 'football' 'basketball' 'kobe' 'league'
 'olympics' 'nba' 'championship' 'baseball' 'team' 'pitcher' 'prix'
 'auburn' 'olympic' 'teams' 'nfl' 'season' 'doping' 'mets' 'cleveland'
 'bryant' 'pacers' 'striker' 'turin' 'tennis' 'redskins' 'expos'
 'champion' 'ncaa' 'motorsport' 'rugby' 'manager' 'yankees' 'players'
 'athletic' 'club' 'notre dame' 'wenger' 'bowl' 'coaches']
```

[106]:
```
#looking at 3rd logistic regression misclassified articles
classification_examples(y_test, lr_3_preds, df_test_2['cleaned_description'])
```

```
Number of misclassifications: 172

1 - associated press curt anderson
Real Label: 0, Predicted Label: 1


2 - columbia c hurricane watch issued south carolina coast saturday forecasters
predicted tropical storm gaston would make landfall near charleston sunday night
Real Label: 0, Predicted Label: 1


3 - sebastian sainsbury warned leeds united chiefs today face stark choice
accepting million bid selling elland road
Real Label: 1, Predicted Label: 0


4 - probably heard one toughest endurance sports around deca ironman km swimming
immediately followed km bicycle ride km run currently world record stands hours
held german housewife nobody else ever finished course hours
Real Label: 0, Predicted Label: 1


5 - three banks go high court london seeking ruling could lead bernie ecclestone
losing control formula one racing
```

```
Real Label: 0, Predicted Label: 1
```

- There was a reduction in precision, but an increase in recall. The F1 score increased marginally with the balanced classes model feature.

Random Forest

very basic RF model - with ngram 1 With the random forest model, we moved away from the PCA reducted feature set as the PCA feature set took signigicant longer to run and had worse results

[107]:
```
start_time = time.time()

# Initialize and train the Random Forest Classifier
rf_classifier = RandomForestClassifier(random_state=42)

#RF model fit
rf_classifier.fit(X_train_1, y_train)

end_time = time.time()

elapsed_time = end_time - start_time
print(f"Elapsed time: {elapsed_time:.4f} seconds")
```

```
Elapsed time: 59.9367 seconds
```

[108]:
```
start_time = time.time()

# Predict on the test set
rf_preds = rf_classifier.predict(X_test_1)

end_time = time.time()

elapsed_time = end_time - start_time
print(f"Elapsed time: {elapsed_time:.4f} seconds")
```

```
Elapsed time: 0.4870 seconds
```

[109]:
```
#rf model evaluation
classification_rep = classification_report(y_test, rf_preds)

print("\nClassification Report:")
print(classification_rep)
```

```
Classification Report:
              precision    recall  f1-score   support
```

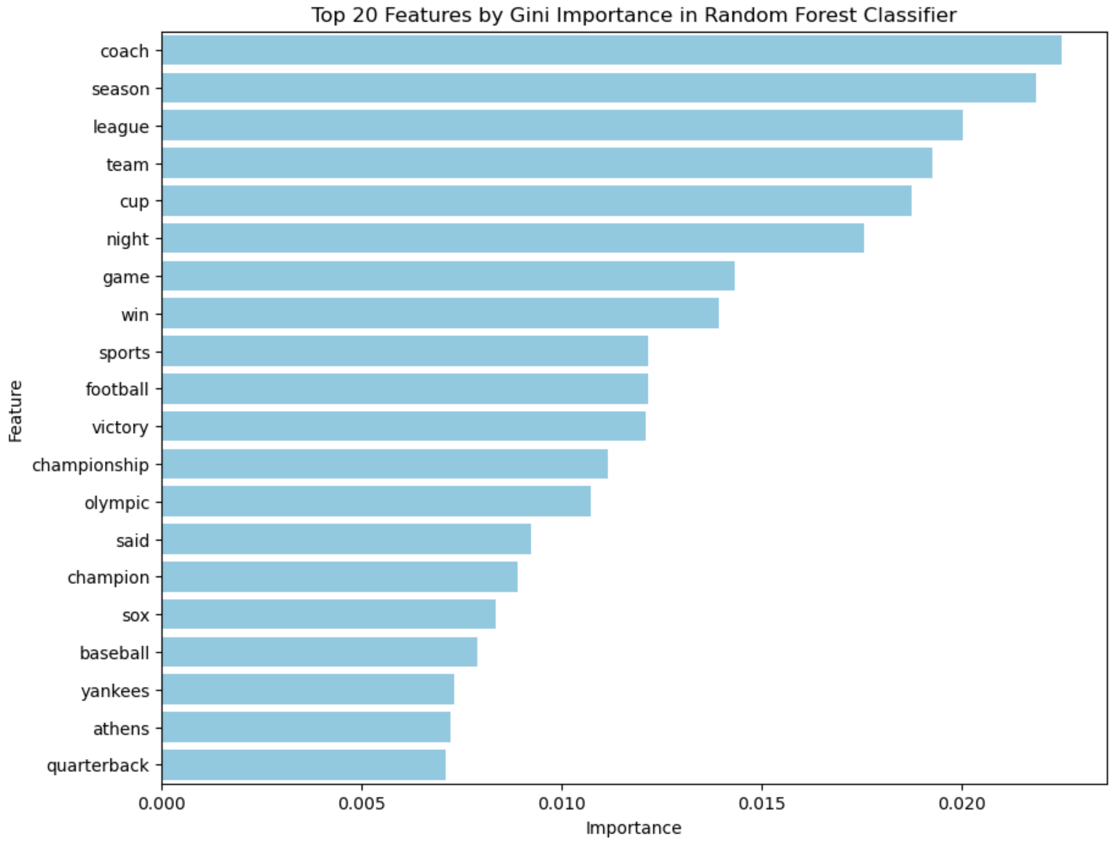
```
           0       0.99      0.98      0.98      5700
           1       0.93      0.96      0.95      1900

    accuracy                           0.97      7600
   macro avg       0.96      0.97      0.96      7600
weighted avg       0.97      0.97      0.97      7600
```

[110]:
```python
f1_score(y_test, rf_preds)
```

[110]: 0.9470129870129869

[111]:
```python
#creating feature df from of all tfidf features
feature_importances = pd.DataFrame({'Feature': tfidf_1.get_feature_names_out(),
 ↪'Importance': rf_classifier.feature_importances_})

#sorting top 20 features from tfidf
top_rf_features = feature_importances.sort_values(by='Importance',
 ↪ascending=False).head(20)
```

[112]:
```python
#ploing top features
plt.figure(figsize=(10, 8))
sns.barplot(x='Importance', y='Feature', data=top_rf_features, color='skyblue')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.title('Top 20 Features by Gini Importance in Random Forest Classifier')
plt.show()
```



[113]:
```
classification_examples(y_test, rf_preds, df_test_2['cleaned_description'])
```

```
Number of misclassifications: 204

1 - associated press curt anderson
Real Label: 0, Predicted Label: 1


2 - columbia c hurricane watch issued south carolina coast saturday forecasters
predicted tropical storm gaston would make landfall near charleston sunday night
Real Label: 0, Predicted Label: 1


3 - china made debut last night club world leading economic powers
asinternational pressure mounts change decade old currency peg critics accuse
giving chinese products unfair competitive edge
Real Label: 0, Predicted Label: 1


4 - everton chairman bill kenwright plans russian revolution goodison park may
thawed cold war director paul gregg
```

```
Real Label: 1, Predicted Label: 0


5 - last six years leominster blue devils endured thanksgiving day filled
frustration instead celebration
Real Label: 1, Predicted Label: 0
```

very basic RF model - with ngram 2

[114]:
```
# Initialize and train the Random Forest Classifier
rf_classifier_2 = RandomForestClassifier(random_state=42)

#RF model fit
rf_classifier_2.fit(X_train_2, y_train)

# Predict on the test set
rf_preds_2 = rf_classifier_2.predict(X_test_2)
```

[115]:
```
#RF model evaluation
classification_rep_2 = classification_report(y_test, rf_preds_2)

print("\nClassification Report:")
print(classification_rep_2)
```

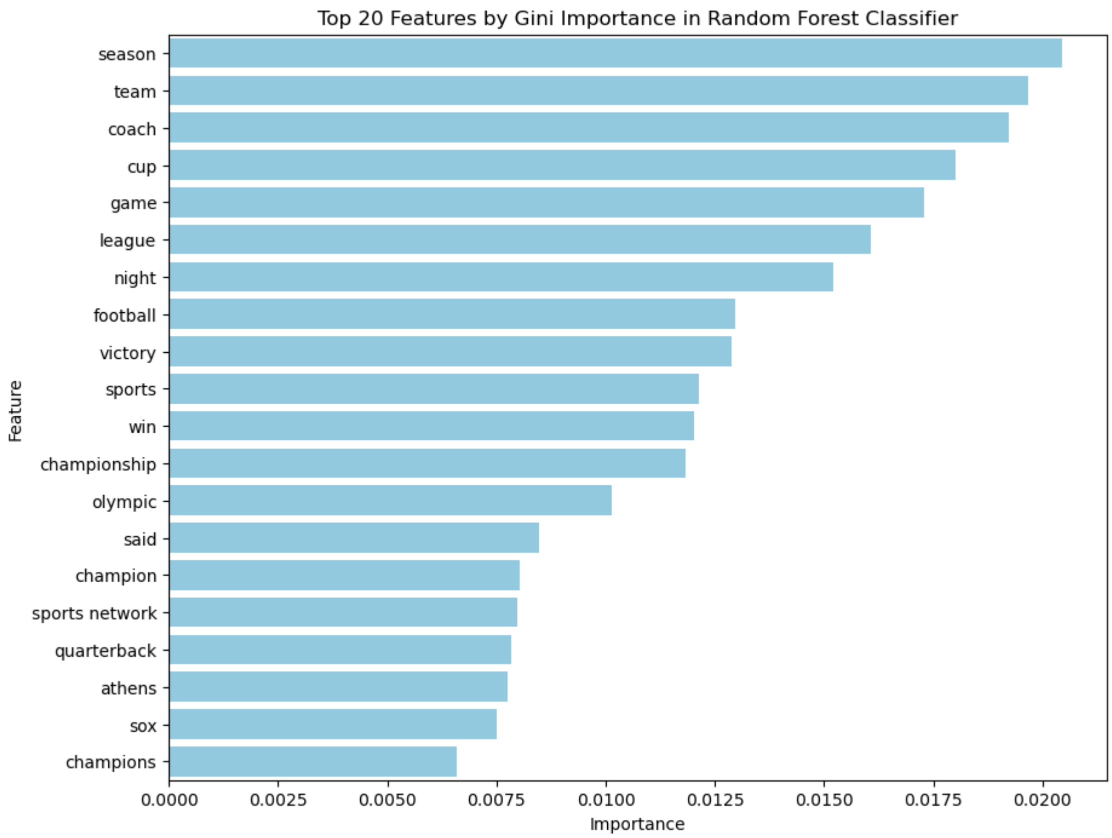
```
Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.98      0.98      5700
           1       0.94      0.96      0.95      1900

    accuracy                           0.97      7600
   macro avg       0.96      0.97      0.97      7600
weighted avg       0.97      0.97      0.97      7600
```

[116]:
```
f1_score(y_test, rf_preds_2)
```

[116]: 0.9490462503266266

[117]:
```
#creating feature df from of all tfidf features
feature_importances_2 = pd.DataFrame({'Feature': tfidf_2.
 ↪get_feature_names_out(), 'Importance': rf_classifier_2.feature_importances_})

#sorting top 20 features from tfidf
top_rf_features_2 = feature_importances_2.sort_values(by='Importance',␣
 ↪ascending=False).head(20)
```

[118]:
```
#ploing top features
plt.figure(figsize=(10, 8))
sns.barplot(x='Importance', y='Feature', data=top_rf_features_2,␣
↪color='skyblue')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.title('Top 20 Features by Gini Importance in Random Forest Classifier')
plt.show()
```



[119]:
```
#misclassification for articles from random forest model 2
classification_examples(y_test, rf_preds_2, df_test_2['cleaned_description'])
```

```
Number of misclassifications: 195

1 - columbia c hurricane watch issued south carolina coast saturday forecasters
predicted tropical storm gaston would make landfall near charleston sunday night
Real Label: 0, Predicted Label: 1


2 - sebastian sainsbury warned leeds united chiefs today face stark choice
accepting million bid selling elland road
```

```
Real Label: 1, Predicted Label: 0


3 - china made debut last night club world leading economic powers
asinternational pressure mounts change decade old currency peg critics accuse
giving chinese products unfair competitive edge
Real Label: 0, Predicted Label: 1


4 - sammy rozenberg ap staff writer boxingscene staff writer boxingscene ready
willing engage conversation post fight press conference following shane mosley
winky wright rematch
Real Label: 1, Predicted Label: 0


5 - probably heard one toughest endurance sports around deca ironman km swimming
immediately followed km bicycle ride km run currently world record stands hours
held german housewife nobody else ever finished course hours
Real Label: 0, Predicted Label: 1
```

1.4 Deep Learning

[120]:
```
#convert series into array data
df_train_np = df_train_2['cleaned_description'].values
df_test_np = df_test_2['cleaned_description'].values

#creating embedding value
max_tokens = 10000
max_sequence_length = 128
embedding_dims = 32
vectorize_layer = TextVectorization(max_tokens=max_tokens,
                                    output_sequence_length=max_sequence_length)
vectorize_layer.adapt(df_train_np)
```

[121]:
```
#create model
model = Sequential()
model.add(vectorize_layer)
model.add(Embedding(max_tokens+1, output_dim=embedding_dims))
model.add(GlobalAveragePooling1D())
model.add(Dense(24, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
model.summary()
```

```
Model: "sequential"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
```

```
=================================================================
 text_vectorization (TextVe  (None, 128)               0
 ctorization)

 embedding (Embedding)       (None, 128, 32)           320032

 global_average_pooling1d (  (None, 32)                0
 GlobalAveragePooling1D)

 dense (Dense)               (None, 24)                792

 dense_1 (Dense)             (None, 1)                 25

=================================================================
Total params: 320849 (1.22 MB)
Trainable params: 320849 (1.22 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[122]:
```
start_time = time.time()

#compiling model
model.compile(loss='binary_crossentropy', optimizer='adam',␣
↪metrics=[Precision(), Recall()])

# Train model
model.fit(df_train_np, y_train, epochs=10, validation_data=(df_test_np, y_test))

end_time = time.time()

elapsed_time = end_time - start_time
print(f"Elapsed time: {elapsed_time:.4f} seconds")
```

```
Epoch 1/10
3750/3750 [==============================] - 5s 1ms/step - loss: 0.1460 -
precision: 0.9530 - recall: 0.8196 - val_loss: 0.0709 - val_precision: 0.9405 -
val_recall: 0.9737
Epoch 2/10
3750/3750 [==============================] - 5s 1ms/step - loss: 0.0559 -
precision: 0.9614 - recall: 0.9722 - val_loss: 0.0636 - val_precision: 0.9491 -
val_recall: 0.9721
Epoch 3/10
3750/3750 [==============================] - 5s 1ms/step - loss: 0.0471 -
precision: 0.9649 - recall: 0.9794 - val_loss: 0.0635 - val_precision: 0.9481 -
val_recall: 0.9716
Epoch 4/10
3750/3750 [==============================] - 4s 1ms/step - loss: 0.0405 -
precision: 0.9679 - recall: 0.9829 - val_loss: 0.0636 - val_precision: 0.9547 -
```

```
val_recall: 0.9642
Epoch 5/10
3750/3750 [==============================] - 4s 1ms/step - loss: 0.0350 -
precision: 0.9717 - recall: 0.9859 - val_loss: 0.0676 - val_precision: 0.9615 -
val_recall: 0.9584
Epoch 6/10
3750/3750 [==============================] - 4s 1ms/step - loss: 0.0306 -
precision: 0.9752 - recall: 0.9876 - val_loss: 0.0707 - val_precision: 0.9624 -
val_recall: 0.9558
Epoch 7/10
3750/3750 [==============================] - 4s 1ms/step - loss: 0.0267 -
precision: 0.9776 - recall: 0.9887 - val_loss: 0.0765 - val_precision: 0.9634 -
val_recall: 0.9547
Epoch 8/10
3750/3750 [==============================] - 4s 1ms/step - loss: 0.0236 -
precision: 0.9795 - recall: 0.9897 - val_loss: 0.0810 - val_precision: 0.9603 -
val_recall: 0.9553
Epoch 9/10
3750/3750 [==============================] - 4s 1ms/step - loss: 0.0206 -
precision: 0.9825 - recall: 0.9913 - val_loss: 0.0848 - val_precision: 0.9554 -
val_recall: 0.9589
Epoch 10/10
3750/3750 [==============================] - 4s 1ms/step - loss: 0.0182 -
precision: 0.9841 - recall: 0.9919 - val_loss: 0.0942 - val_precision: 0.9632 -
val_recall: 0.9505
Elapsed time: 44.4028 seconds
```

[123]:
```
#predictions
nn_probs = model.predict(df_test_np)
```

```
238/238 [==============================] - 0s 374us/step
```

[124]:
```
#converting probababilities into values using .5 as the threshold
nn_pred = (nn_probs > 0.5).astype(int).flatten()

nn_pred
```

[124]:
```
array([1, 0, 0, …, 0, 0, 1])
```

[125]:
```
#viewing classification report
nn_class_rep=classification_report(y_test, nn_pred)

print(nn_class_rep)
```

```
              precision    recall  f1-score   support

           0       0.98      0.99      0.99      5700
           1       0.96      0.95      0.96      1900
```

```
    accuracy                           0.98      7600
   macro avg       0.97      0.97      0.97      7600
weighted avg       0.98      0.98      0.98      7600
```

[126]:
```
f1_score(y_test, nn_pred)
```

[126]: 0.9568211920529801

[127]:
```
#misclassification of articles from feed forward neural net
classification_examples(y_test, nn_pred, df_test_2['cleaned_description'])
```

```
Number of misclassifications: 163

1 - associated press curt anderson
Real Label: 0, Predicted Label: 1


2 - probably heard one toughest endurance sports around deca ironman km swimming
immediately followed km bicycle ride km run currently world record stands hours
held german housewife nobody else ever finished course hours
Real Label: 0, Predicted Label: 1


3 - three banks go high court london seeking ruling could lead bernie ecclestone
losing control formula one racing
Real Label: 0, Predicted Label: 1


4 - playing best golf year season ending tour championship tiger woods shoots
leaving tied jay haas
Real Label: 1, Predicted Label: 0


5 - everton chairman bill kenwright plans russian revolution goodison park may
thawed cold war director paul gregg
Real Label: 1, Predicted Label: 0
```

CNN Model

[128]:
```
#instantiating a 1D cnn model
cnn = Sequential()
#adding the vecortized layer of data
cnn.add(vectorize_layer)
#setting the embedding inputs
cnn.add(Embedding(input_dim=10001, output_dim=64))
```

```
#adding a convolutional layer with 64 filters, window size of 5 and padding the␣
↪same
cnn.add(Conv1D(filters=64, kernel_size=5, padding='same'))
cnn.add(Flatten())
cnn.add(Dense(1, activation='sigmoid'))
cnn.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 text_vectorization (TextVe  (None, 128)               0
 ctorization)

 embedding_1 (Embedding)     (None, 128, 64)           640064

 conv1d (Conv1D)             (None, 128, 64)           20544

 flatten (Flatten)           (None, 8192)              0

 dense_2 (Dense)             (None, 1)                 8193

=================================================================
Total params: 668801 (2.55 MB)
Trainable params: 668801 (2.55 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[129]:

```
start_time = time.time()

#compiling model
cnn.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=[Precision(), Recall()])
#setting early stopping
early_stopping = EarlyStopping(monitor='val_loss', patience=5)

#fitting model with epochs of 100 and batchsize of 128
cnn.fit(df_train_np, y_train,
        epochs=50, batch_size=512,
        validation_data=(df_test_np, y_test),
        callbacks=[early_stopping])

end_time = time.time()

elapsed_time = end_time - start_time
print(f"Elapsed time: {elapsed_time:.4f} seconds")
```

```
Epoch 1/50
235/235 [==============================] - 8s 33ms/step - loss: 0.1551 -
precision_1: 0.9546 - recall_1: 0.7926 - val_loss: 0.0668 - val_precision_1:
0.9530 - val_recall_1: 0.9595
Epoch 2/50
235/235 [==============================] - 8s 33ms/step - loss: 0.0488 -
precision_1: 0.9662 - recall_1: 0.9707 - val_loss: 0.0646 - val_precision_1:
0.9644 - val_recall_1: 0.9553
Epoch 3/50
235/235 [==============================] - 8s 33ms/step - loss: 0.0379 -
precision_1: 0.9737 - recall_1: 0.9778 - val_loss: 0.0706 - val_precision_1:
0.9501 - val_recall_1: 0.9611
Epoch 4/50
235/235 [==============================] - 8s 33ms/step - loss: 0.0293 -
precision_1: 0.9800 - recall_1: 0.9846 - val_loss: 0.0767 - val_precision_1:
0.9518 - val_recall_1: 0.9553
Epoch 5/50
235/235 [==============================] - 8s 33ms/step - loss: 0.0197 -
precision_1: 0.9869 - recall_1: 0.9904 - val_loss: 0.0918 - val_precision_1:
0.9552 - val_recall_1: 0.9426
Epoch 6/50
235/235 [==============================] - 8s 33ms/step - loss: 0.0113 -
precision_1: 0.9926 - recall_1: 0.9946 - val_loss: 0.1101 - val_precision_1:
0.9541 - val_recall_1: 0.9411
Epoch 7/50
235/235 [==============================] - 8s 33ms/step - loss: 0.0060 -
precision_1: 0.9973 - recall_1: 0.9979 - val_loss: 0.1336 - val_precision_1:
0.9449 - val_recall_1: 0.9484
Elapsed time: 54.9135 seconds
```

[130]:
```python
cnn_probs = cnn.predict(df_test_np)

cnn_pred = (cnn_probs > 0.5).astype(int).flatten()

#creating classification report
cnn_class_rep = classification_report(y_test, cnn_pred)

print(cnn_class_rep)
```

```
238/238 [==============================] - 0s 938us/step
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      5700
           1       0.94      0.95      0.95      1900

    accuracy                           0.97      7600
   macro avg       0.96      0.97      0.96      7600
weighted avg       0.97      0.97      0.97      7600
```

[131]:
```
f1_score(y_test, cnn_pred)
```

[131]: 0.9466771736275282

[132]:
```
classification_examples(y_test, cnn_pred, df_test_2['cleaned_description'])
```

```
Number of misclassifications: 203

1 - years shawsheen tech greater lowell battled william j collins cup
thanksgiving day
Real Label: 1, Predicted Label: 0


2 - electronic arts announced exclusive licensing relationships national
football league players inc develop publish distribute interactive football
games
Real Label: 1, Predicted Label: 0


3 - probably heard one toughest endurance sports around deca ironman km swimming
immediately followed km bicycle ride km run currently world record stands hours
held german housewife nobody else ever finished course hours
Real Label: 0, Predicted Label: 1


4 - three banks go high court london seeking ruling could lead bernie ecclestone
losing control formula one racing
Real Label: 0, Predicted Label: 1


5 - brussels turkey recognize republic cyprus tacitly wants begin membership
negotiations european union according draft document leaked monday
Real Label: 0, Predicted Label: 1
```

Simple RNN

[133]:
```
#creating simple_rnn with required layers
embedding_dims = 128

simple_rnn = Sequential()
simple_rnn.add(vectorize_layer)
simple_rnn.add(Embedding(max_tokens + 1, embedding_dims))
simple_rnn.add(SimpleRNN(128, return_sequences=False))
simple_rnn.add(Dense(100, activation='relu'))
simple_rnn.add(Dropout(.5))
```

```
simple_rnn.add(Dense(100, activation='relu'))
simple_rnn.add(Dropout(.5))
simple_rnn.add(Dense(1, activation='sigmoid'))
simple_rnn.summary()
```

```
Model: "sequential_2"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 text_vectorization (TextVe  (None, 128)               0
 ctorization)

 embedding_2 (Embedding)     (None, 128, 128)          1280128

 simple_rnn (SimpleRNN)      (None, 128)               32896

 dense_3 (Dense)             (None, 100)               12900

 dropout (Dropout)           (None, 100)               0

 dense_4 (Dense)             (None, 100)               10100

 dropout_1 (Dropout)         (None, 100)               0

 dense_5 (Dense)             (None, 1)                 101

=================================================================
Total params: 1336125 (5.10 MB)
Trainable params: 1336125 (5.10 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[134]:
```
start_time = time.time()

simple_rnn.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=[Precision(), Recall()])

early_stopping = EarlyStopping(monitor='val_loss',
                               patience=5,
                               restore_best_weights=True)

simple_rnn.fit(df_train_np, y_train, epochs=50, batch_size=5000,
          validation_data=(df_test_np, y_test),
              callbacks=[early_stopping])

end_time = time.time()
```

```python
elapsed_time = end_time - start_time
print(f"Elapsed time: {elapsed_time:.4f} seconds")
```

```
Epoch 1/50
24/24 [==============================] - 11s 438ms/step - loss: 0.5959 -
precision_2: 0.2044 - recall_2: 0.0179 - val_loss: 0.5604 - val_precision_2:
0.0000e+00 - val_recall_2: 0.0000e+00
Epoch 2/50
24/24 [==============================] - 11s 443ms/step - loss: 0.5780 -
precision_2: 0.2424 - recall_2: 0.0011 - val_loss: 0.5680 - val_precision_2:
0.0000e+00 - val_recall_2: 0.0000e+00
Epoch 3/50
24/24 [==============================] - 11s 440ms/step - loss: 0.5353 -
precision_2: 0.5052 - recall_2: 0.0177 - val_loss: 0.4408 - val_precision_2:
0.0000e+00 - val_recall_2: 0.0000e+00
Epoch 4/50
24/24 [==============================] - 10s 435ms/step - loss: 0.5678 -
precision_2: 0.4079 - recall_2: 0.3984 - val_loss: 0.4673 - val_precision_2:
0.7531 - val_recall_2: 0.4784
Epoch 5/50
24/24 [==============================] - 11s 442ms/step - loss: 0.5292 -
precision_2: 0.3022 - recall_2: 0.0426 - val_loss: 0.3805 - val_precision_2:
0.7082 - val_recall_2: 0.5353
Epoch 6/50
24/24 [==============================] - 11s 441ms/step - loss: 0.3895 -
precision_2: 0.6414 - recall_2: 0.4991 - val_loss: 0.6769 - val_precision_2:
0.2129 - val_recall_2: 0.2037
Epoch 7/50
24/24 [==============================] - 11s 447ms/step - loss: 0.4191 -
precision_2: 0.6315 - recall_2: 0.5473 - val_loss: 0.3262 - val_precision_2:
0.7155 - val_recall_2: 0.8021
Epoch 8/50
24/24 [==============================] - 11s 442ms/step - loss: 0.2595 -
precision_2: 0.7856 - recall_2: 0.8449 - val_loss: 0.2595 - val_precision_2:
0.7815 - val_recall_2: 0.8489
Epoch 9/50
24/24 [==============================] - 10s 428ms/step - loss: 0.2177 -
precision_2: 0.8277 - recall_2: 0.8773 - val_loss: 0.2553 - val_precision_2:
0.7940 - val_recall_2: 0.8400
Epoch 10/50
24/24 [==============================] - 10s 429ms/step - loss: 0.1958 -
precision_2: 0.8511 - recall_2: 0.8874 - val_loss: 0.2480 - val_precision_2:
0.8032 - val_recall_2: 0.8526
Epoch 11/50
24/24 [==============================] - 10s 433ms/step - loss: 0.1854 -
precision_2: 0.8588 - recall_2: 0.8966 - val_loss: 0.2444 - val_precision_2:
0.8099 - val_recall_2: 0.8500
```

```
Epoch 12/50
24/24 [==============================] - 10s 432ms/step - loss: 0.1741 -
precision_2: 0.8735 - recall_2: 0.8998 - val_loss: 0.2447 - val_precision_2:
0.8104 - val_recall_2: 0.8347
Epoch 13/50
24/24 [==============================] - 11s 440ms/step - loss: 0.1680 -
precision_2: 0.8771 - recall_2: 0.9039 - val_loss: 0.2451 - val_precision_2:
0.8149 - val_recall_2: 0.8458
Epoch 14/50
24/24 [==============================] - 11s 438ms/step - loss: 0.1688 -
precision_2: 0.8745 - recall_2: 0.9039 - val_loss: 0.2510 - val_precision_2:
0.7971 - val_recall_2: 0.8684
Epoch 15/50
24/24 [==============================] - 10s 436ms/step - loss: 0.3193 -
precision_2: 0.7473 - recall_2: 0.7594 - val_loss: 0.2839 - val_precision_2:
0.7935 - val_recall_2: 0.8232
Epoch 16/50
24/24 [==============================] - 11s 439ms/step - loss: 0.1990 -
precision_2: 0.8525 - recall_2: 0.8876 - val_loss: 0.2542 - val_precision_2:
0.8094 - val_recall_2: 0.8584
Elapsed time: 168.3582 seconds
```

[135]:
```
#creating probability predictions
rnn_probs = simple_rnn.predict(df_test_np)

#converting to binary predictions with .5 probability as threshold
rnn_pred = (rnn_probs > 0.5).astype(int).flatten()

#creating classification report
rnn_class_rep = classification_report(y_test, rnn_pred)

print(rnn_class_rep)
```

```
238/238 [==============================] - 1s 5ms/step
              precision    recall  f1-score   support

           0       0.95      0.93      0.94      5700
           1       0.81      0.85      0.83      1900

    accuracy                           0.91      7600
   macro avg       0.88      0.89      0.89      7600
weighted avg       0.91      0.91      0.91      7600
```

[136]:
```
f1_score(y_test, rnn_pred)
```

[136]: 0.8294812532100668

[137]:
```
classification_examples(y_test, rnn_pred, df_test_2['cleaned_description'])
```

```
Number of misclassifications: 664

1 - individually theyve unstoppable respective industries theyre legends
survived dot com burst came winners
Real Label: 0, Predicted Label: 1


2 - scott mcgregor former head royal philips electronics semiconductor division
replace alan ross plans retire
Real Label: 0, Predicted Label: 1


3 - years shawsheen tech greater lowell battled william j collins cup
thanksgiving day
Real Label: 1, Predicted Label: 0


4 - ap calling unlv gold mine mike sanford took coach runnin rebels monday two
years offensive coordinator high scoring utah
Real Label: 1, Predicted Label: 0


5 - somber tones professional adjectives president athletic director longer
football coach took turns announcing university florida firing monday surprising
coming sooner rather later
Real Label: 1, Predicted Label: 0
```

- The simple rnn model is not an improvement on a basic feed forward network

LSTM Neural Net Model

[138]:
```
#creating lstm rnn with 128 embededded dims, dense layer of 200 neurons,␣
↪dropout, and an addtional layer of just 50 neurons
embedding_dims = 128

lstm = Sequential()
lstm.add(vectorize_layer)
lstm.add(Embedding(max_tokens + 1, embedding_dims))
lstm.add(LSTM(100, return_sequences=False))
lstm.add(Dense(200, activation='relu'))
lstm.add(Dropout(.5))
# lstm.add(Dense(100, activation='relu'))
# lstm.add(Dropout(.5))
lstm.add(Dense(50, activation='relu'))
# lstm.add(Dropout(.5))
```

```python
lstm.add(Dense(1, activation='sigmoid'))
lstm.summary()
```

```
Model: "sequential_3"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 text_vectorization (TextVe  (None, 128)               0
 ctorization)

 embedding_3 (Embedding)     (None, 128, 128)          1280128

 lstm (LSTM)                 (None, 100)               91600

 dense_6 (Dense)             (None, 200)               20200

 dropout_2 (Dropout)         (None, 200)               0

 dense_7 (Dense)             (None, 50)                10050

 dense_8 (Dense)             (None, 1)                 51

=================================================================
Total params: 1402029 (5.35 MB)
Trainable params: 1402029 (5.35 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[139]:
```python
start_time = time.time()

#compiling
lstm.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=[Precision(), Recall()])

#early stopping with patience of 3
early_stopping = EarlyStopping(monitor='val_loss',
                               patience=5,
                               restore_best_weights=True)

#fitting model with 50 epochs and batch size of 5000
lstm.fit(df_train_np, y_train, epochs=50, batch_size=5000,
          validation_data=(df_test_np, y_test),
              callbacks=[early_stopping])

end_time = time.time()
```

```
elapsed_time = end_time - start_time
print(f"Elapsed time: {elapsed_time:.4f} seconds")
```

```
Epoch 1/50
24/24 [==============================] - 29s 1s/step - loss: 0.5946 -
precision_3: 0.2639 - recall_3: 0.0081 - val_loss: 0.5626 - val_precision_3:
0.0000e+00 - val_recall_3: 0.0000e+00
Epoch 2/50
24/24 [==============================] - 28s 1s/step - loss: 0.5650 -
precision_3: 0.0000e+00 - recall_3: 0.0000e+00 - val_loss: 0.5624 -
val_precision_3: 0.0000e+00 - val_recall_3: 0.0000e+00
Epoch 3/50
24/24 [==============================] - 28s 1s/step - loss: 0.5643 -
precision_3: 0.0000e+00 - recall_3: 0.0000e+00 - val_loss: 0.5624 -
val_precision_3: 0.0000e+00 - val_recall_3: 0.0000e+00
Epoch 4/50
24/24 [==============================] - 28s 1s/step - loss: 0.5638 -
precision_3: 0.0000e+00 - recall_3: 0.0000e+00 - val_loss: 0.5623 -
val_precision_3: 0.0000e+00 - val_recall_3: 0.0000e+00
Epoch 5/50
24/24 [==============================] - 29s 1s/step - loss: 0.5637 -
precision_3: 0.0000e+00 - recall_3: 0.0000e+00 - val_loss: 0.5623 -
val_precision_3: 0.0000e+00 - val_recall_3: 0.0000e+00
Epoch 6/50
24/24 [==============================] - 29s 1s/step - loss: 0.5636 -
precision_3: 0.0000e+00 - recall_3: 0.0000e+00 - val_loss: 0.5624 -
val_precision_3: 0.0000e+00 - val_recall_3: 0.0000e+00
Epoch 7/50
24/24 [==============================] - 28s 1s/step - loss: 0.5639 -
precision_3: 0.0000e+00 - recall_3: 0.0000e+00 - val_loss: 0.5628 -
val_precision_3: 0.0000e+00 - val_recall_3: 0.0000e+00
Epoch 8/50
24/24 [==============================] - 28s 1s/step - loss: 0.5637 -
precision_3: 0.0000e+00 - recall_3: 0.0000e+00 - val_loss: 0.5625 -
val_precision_3: 0.0000e+00 - val_recall_3: 0.0000e+00
Epoch 9/50
24/24 [==============================] - 28s 1s/step - loss: 0.5633 -
precision_3: 0.0000e+00 - recall_3: 0.0000e+00 - val_loss: 0.5623 -
val_precision_3: 0.0000e+00 - val_recall_3: 0.0000e+00
Epoch 10/50
24/24 [==============================] - 28s 1s/step - loss: 0.5635 -
precision_3: 0.0000e+00 - recall_3: 0.0000e+00 - val_loss: 0.5625 -
val_precision_3: 0.0000e+00 - val_recall_3: 0.0000e+00
Elapsed time: 284.0194 seconds
```

[140]:
```
#creating probability predictions
lstm_probs = lstm.predict(df_test_np)
```

```
#converting to binary predictions with .5 probability as threshold
lstm_preds = (lstm_probs > 0.5).astype(int).flatten()

#creating classification report
lstm_class_rep = classification_report(y_test, lstm_preds)

print(lstm_class_rep)
```

```
238/238 [==============================] - 5s 19ms/step
              precision    recall  f1-score   support

           0       0.75      1.00      0.86      5700
           1       0.00      0.00      0.00      1900

    accuracy                           0.75      7600
   macro avg       0.38      0.50      0.43      7600
weighted avg       0.56      0.75      0.64      7600


/Users/travisdarby/anaconda3/lib/python3.11/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))
/Users/travisdarby/anaconda3/lib/python3.11/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))
/Users/travisdarby/anaconda3/lib/python3.11/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))
```

[141]:
```
f1_score(y_test, lstm_preds)
```

[141]: 0.0

[142]:
```
classification_examples(y_test, lstm_preds, df_test_2['cleaned_description'])
```

```
Number of misclassifications: 1900

1 - charlotte n c sports network carolina panthers running back stephen davis
miss remainder season placed injured reserve saturday
Real Label: 1, Predicted Label: 0
```

```
2 - daniel vettori spun new zealand brink crushing victory bangladesh second
final test aziz stadium chittagong today
Real Label: 1, Predicted Label: 0


3 - annika sorenstam could manage level par day three adt tour championship
florida enough maintain one stroke lead
Real Label: 1, Predicted Label: 0


4 - ap maria sharapova withdrew semifinal advanta championships saturday
strained right shoulder
Real Label: 1, Predicted Label: 0


5 - spectators watching ground eyes europe trained romes olympic stadium tonight
real madrid seek win probably need avoid humiliating early exit champions league
Real Label: 1, Predicted Label: 0
```

[143]:
```
#creating lstm rnn with 128 embededded dims, dense layer of 200 neurons,␣
↪dropout, and an addtional layer of just 50 neurons
embedding_dims = 128

lstm_2 = Sequential()
lstm_2.add(vectorize_layer)
lstm_2.add(Embedding(max_tokens + 1, embedding_dims))
lstm_2.add(LSTM(100, return_sequences=False))
lstm_2.add(Dense(200, activation='relu'))
# lstm.add(Dropout(.5))
# lstm.add(Dense(100, activation='relu'))
# lstm.add(Dropout(.5))
lstm_2.add(Dense(50, activation='relu'))
# lstm.add(Dropout(.5))
lstm_2.add(Dense(1, activation='sigmoid'))
lstm_2.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 text_vectorization (TextVe  (None, 128)               0
 ctorization)

 embedding_4 (Embedding)     (None, 128, 128)          1280128

 lstm_1 (LSTM)               (None, 100)               91600
```

```
 dense_9 (Dense)             (None, 200)               20200

 dense_10 (Dense)            (None, 50)                10050

 dense_11 (Dense)            (None, 1)                 51

=================================================================
Total params: 1402029 (5.35 MB)
Trainable params: 1402029 (5.35 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[144]:

```
start_time = time.time()

#compiling
lstm_2.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=[Precision(), Recall()])

#early stopping with patience of 3
early_stopping = EarlyStopping(monitor='val_loss',
                               patience=5,
                               restore_best_weights=True)

#fitting model with 50 epochs and batch size of 5000
lstm_2.fit(df_train_np, y_train, epochs=50, batch_size=5000,
          validation_data=(df_test_np, y_test),
              callbacks=[early_stopping])

end_time = time.time()

elapsed_time = end_time - start_time
print(f"Elapsed time: {elapsed_time:.4f} seconds")
```

```
Epoch 1/50
24/24 [==============================] - 29s 1s/step - loss: 0.5905 -
precision_4: 0.0000e+00 - recall_4: 0.0000e+00 - val_loss: 0.5632 -
val_precision_4: 0.0000e+00 - val_recall_4: 0.0000e+00
Epoch 2/50
24/24 [==============================] - 28s 1s/step - loss: 0.5626 -
precision_4: 0.0000e+00 - recall_4: 0.0000e+00 - val_loss: 0.5623 -
val_precision_4: 0.0000e+00 - val_recall_4: 0.0000e+00
Epoch 3/50
24/24 [==============================] - 28s 1s/step - loss: 0.5624 -
precision_4: 0.0000e+00 - recall_4: 0.0000e+00 - val_loss: 0.5623 -
val_precision_4: 0.0000e+00 - val_recall_4: 0.0000e+00
Epoch 4/50
```

```
24/24 [==============================] - 28s 1s/step - loss: 0.5624 -
precision_4: 0.0000e+00 - recall_4: 0.0000e+00 - val_loss: 0.5624 -
val_precision_4: 0.0000e+00 - val_recall_4: 0.0000e+00
Epoch 5/50
24/24 [==============================] - 28s 1s/step - loss: 0.5625 -
precision_4: 0.0000e+00 - recall_4: 0.0000e+00 - val_loss: 0.5623 -
val_precision_4: 0.0000e+00 - val_recall_4: 0.0000e+00
Epoch 6/50
24/24 [==============================] - 28s 1s/step - loss: 0.5624 -
precision_4: 0.0000e+00 - recall_4: 0.0000e+00 - val_loss: 0.5625 -
val_precision_4: 0.0000e+00 - val_recall_4: 0.0000e+00
Epoch 7/50
24/24 [==============================] - 28s 1s/step - loss: 0.5624 -
precision_4: 0.0000e+00 - recall_4: 0.0000e+00 - val_loss: 0.5629 -
val_precision_4: 0.0000e+00 - val_recall_4: 0.0000e+00
Elapsed time: 197.4014 seconds
```

[145]:
```python
#creating probability predictions
lstm_2_probs = lstm_2.predict(df_test_np)

#converting to binary predictions with .5 probability as threshold
lstm_2_preds = (lstm_2_probs > 0.5).astype(int).flatten()

#creating classification report
lstm_2_class_rep = classification_report(y_test, lstm_2_preds)

print(lstm_2_class_rep)
```

```
238/238 [==============================] - 5s 22ms/step
              precision    recall  f1-score   support

           0       0.75      1.00      0.86      5700
           1       0.00      0.00      0.00      1900

    accuracy                           0.75      7600
   macro avg       0.38      0.50      0.43      7600
weighted avg       0.56      0.75      0.64      7600


/Users/travisdarby/anaconda3/lib/python3.11/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))
/Users/travisdarby/anaconda3/lib/python3.11/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))
```

```
/Users/travisdarby/anaconda3/lib/python3.11/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))
```

re-sampled datasets to create balanced classes in the training data

[146]:
```
#splitting data into minoriry or majority classes

majority_class = df_train_2[df_train_2['label']==0]
minority_class = df_train_2[df_train_2['label']==1]
```

[147]:
```
#undersampling the majority classes to match the minority class
undersampled_majority_class = majority_class.sample(len(minority_class),␣
 ↪replace=True, random_state=1842)
```

[148]:
```
undersampled_majority_class.shape
```

[148]:
```
(30000, 5)
```

[149]:
```
minority_class.shape
```

[149]:
```
(30000, 5)
```

[150]:
```
#creating df with even classes from oversampled minoroty class
#combining the datasets, then resampling the data randomly as to prevent data␣
 ↪from being stacked
undersampled_combined_df = pd.concat([undersampled_majority_class,␣
 ↪minority_class]).sample(frac=1, random_state=1842).reset_index(drop=True)
```

[151]:
```
#finding the proportion of sports articles to non
len(undersampled_combined_df[undersampled_combined_df['label']==1])/
 ↪len(undersampled_combined_df)
```

[151]:
```
0.5
```

[152]:
```
#creating new training data from undersampled majority class combined df
undersampled_train_np = undersampled_combined_df['cleaned_description'].values
undersampled_y_train = undersampled_combined_df['label']
```

[153]:
```
#creating embedding value
max_tokens = 10000
max_sequence_length = 128

vectorize_layer_2 = TextVectorization(max_tokens=max_tokens,
                                    output_sequence_length=max_sequence_length)
vectorize_layer_2.adapt(undersampled_train_np)
```

[154]:
```
#creating lstm rnn with 128 embededded dims, dense layer of 200 neurons,␣
↪dropout, and an addtional layer of just 50 neurons
embedding_dims = 128

lstm_3 = Sequential()
lstm_3.add(vectorize_layer_2)
lstm_3.add(Embedding(max_tokens + 1, embedding_dims))
lstm_3.add(LSTM(100, return_sequences=False))
lstm_3.add(Dense(200, activation='relu'))
# lstm.add(Dropout(.5))
# lstm.add(Dense(100, activation='relu'))
# lstm.add(Dropout(.5))
lstm_3.add(Dense(50, activation='relu'))
# lstm.add(Dropout(.5))
lstm_3.add(Dense(1, activation='sigmoid'))
lstm_3.summary()
```

```
Model: "sequential_5"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 text_vectorization_1 (Text  (None, 128)               0
 Vectorization)

 embedding_5 (Embedding)     (None, 128, 128)          1280128

 lstm_2 (LSTM)               (None, 100)               91600

 dense_12 (Dense)            (None, 200)               20200

 dense_13 (Dense)            (None, 50)                10050

 dense_14 (Dense)            (None, 1)                 51

=================================================================
Total params: 1402029 (5.35 MB)
Trainable params: 1402029 (5.35 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[155]:
```
start_time = time.time()

#compiling
lstm_3.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=[Precision(), Recall()])
```

```python
#early stopping with patience of 5
early_stopping = EarlyStopping(monitor='val_loss',
                               patience=5,
                               restore_best_weights=True)

#fitting model with 50 epochs and batch size of 5000
lstm_3.fit(undersampled_train_np, undersampled_y_train,
           epochs=50, batch_size=5000,
           validation_data=(df_test_np, y_test),
           callbacks=[early_stopping])

end_time = time.time()

elapsed_time = end_time - start_time
print(f"Elapsed time: {elapsed_time:.4f} seconds")
```

```
Epoch 1/50
12/12 [==============================] - 16s 1s/step - loss: 0.6933 -
precision_5: 0.4989 - recall_5: 0.4989 - val_loss: 0.6878 - val_precision_5:
0.0000e+00 - val_recall_5: 0.0000e+00
Epoch 2/50
12/12 [==============================] - 14s 1s/step - loss: 0.6932 -
precision_5: 0.5019 - recall_5: 0.2510 - val_loss: 0.6987 - val_precision_5:
0.2500 - val_recall_5: 1.0000
Epoch 3/50
12/12 [==============================] - 15s 1s/step - loss: 0.6931 -
precision_5: 0.5006 - recall_5: 0.8343 - val_loss: 0.6868 - val_precision_5:
0.0000e+00 - val_recall_5: 0.0000e+00
Epoch 4/50
12/12 [==============================] - 14s 1s/step - loss: 0.6932 -
precision_5: 0.5006 - recall_5: 0.3338 - val_loss: 0.6966 - val_precision_5:
0.2500 - val_recall_5: 1.0000
Epoch 5/50
12/12 [==============================] - 15s 1s/step - loss: 0.6932 -
precision_5: 0.5008 - recall_5: 0.3339 - val_loss: 0.6924 - val_precision_5:
0.0000e+00 - val_recall_5: 0.0000e+00
Epoch 6/50
12/12 [==============================] - 15s 1s/step - loss: 0.6932 -
precision_5: 0.4995 - recall_5: 0.9158 - val_loss: 0.6917 - val_precision_5:
0.0000e+00 - val_recall_5: 0.0000e+00
Epoch 7/50
12/12 [==============================] - 14s 1s/step - loss: 0.6932 -
precision_5: 0.4963 - recall_5: 0.4963 - val_loss: 0.6919 - val_precision_5:
0.0000e+00 - val_recall_5: 0.0000e+00
Epoch 8/50
12/12 [==============================] - 15s 1s/step - loss: 0.6932 -
precision_5: 0.4956 - recall_5: 0.3304 - val_loss: 0.6919 - val_precision_5:
0.0000e+00 - val_recall_5: 0.0000e+00
```

```
Elapsed time: 117.1195 seconds
```

[156]:

```
#creating probability predictions
lstm_3_probs = lstm_3.predict(df_test_np)

#converting to binary predictions with .5 probability as threshold
lstm_3_preds = (lstm_3_probs > 0.5).astype(int).flatten()

#creating classification report
lstm_3_class_rep = classification_report(y_test, lstm_3_preds)

print(lstm_2_class_rep)
```

```
238/238 [==============================] - 5s 19ms/step
              precision    recall  f1-score   support

           0       0.75      1.00      0.86      5700
           1       0.00      0.00      0.00      1900

    accuracy                           0.75      7600
   macro avg       0.38      0.50      0.43      7600
weighted avg       0.56      0.75      0.64      7600

/Users/travisdarby/anaconda3/lib/python3.11/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))
/Users/travisdarby/anaconda3/lib/python3.11/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))
/Users/travisdarby/anaconda3/lib/python3.11/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))
```

- Overall we were very surprised that the neural net models did not outperform the either of the base models.

We would suggest using a logistic regression model for it simplicity, its interpretability and that fact it won't need massive amounts of computing power.