ECON 626 Prediction Competition 6 Code

Objective: To predict using classification which of the 15,578 text snippets from news articles include the words “economic”,“economy”, “economics” or the character sequence “econom” (not case-sensitive) in it.

Importing libraries

In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings("ignore")

from sklearn.preprocessing import LabelEncoder

import nltk
from nltk.stem import PorterStemmer
from nltk import LancasterStemmer
from nltk.stem import WordNetLemmatizer
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.metrics import edit_distance
import string
import re
from bs4 import BeautifulSoup

from wordcloud import WordCloud

from collections import Counter

from sklearn.model_selection import train_test_split

from sklearn.feature_extraction.text import CountVectorizer

from sklearn.feature_extraction.text import TfidfTransformer

from sklearn import preprocessing

from sklearn import svm
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, classi

from sklearn.model_selection import GridSearchCV

from scipy.sparse import hstack

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confusion
from tensorflow.keras.utils import to_categorical
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Input
```

Importing data

In [ ]:
```
data_path = "/Users/andrew/Downloads/UW courses/ECON 626/Prediction Competit
text_df= pd.read_csv(data_path)
#create a dataframe for our text dataset
```

Note I made two alterations to the dataset pre importing. They are listed below:

- First I added a header to the dataset called 'text'
- After searching for duplicates I found that some of the text started with "=--" which created an error with the csv after saving where some of the values turned to '#NAME'
- I deleted a '<' in line 12575 in the data since the symbol was causing an error where it believed the text inside the symbol was html text and missed an 'econom' sequence. I will look into switch from an 'anything in a <>' regex to a 'specific html commands' regex since this could cause problems in predictions.

In [ ]:
```
text_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15578 entries, 0 to 15577
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   text    15578 non-null  object
dtypes: object(1)
memory usage: 121.8+ KB
```

In [ ]:
```
text_df.head()
```

Out[ ]:

	text
0	CEA believe that some special factors, such as...
1	approved a $282.6 billion measure to fund the ...
2	(AP) ≣ÛÓ An unexpectedly quick rise in. the pr...
3	$17.28 million would be put into a reserve for...
4	Reserve policy makers voted to keep short-term...

Data Cleaning

In [ ]:
```
num_na = text_df.isna().sum()
num_na
```

Out[ ]:
```
text    0
dtype: int64
```

In [ ]:
```
duplicate_rows = text_df.duplicated(keep=False)

# Check if there are any duplicates
if duplicate_rows.any():
    print(text_df[duplicate_rows])
    # Print the rows that are duplicates
else:
    print("No duplicates found.")
```

```
                                                   text
506    general manager, said Silicon Valley's patent ...
1532   yet to damp innovation in Silicon Valley, at l...
1559   way in what central banks are and what they do...
3469   general manager, said Silicon Valley's patent ...
4255   bond market intensified Thursday, as the gap b...
5837   the 1990s, when government spending and taxes ...
7375   Americans to gamble that the U.S. economy can ...
7539   yet to damp innovation in Silicon Valley, at l...
8196   inflation fears on the rise, investors may wan...
8563   from the recession and the collapsed real esta...
8621   bond market intensified Thursday, as the gap b...
9100   Americans to gamble that the U.S. economy can ...
10721  way in what central banks are and what they do...
11204  on both domestic and foreign policy.</br></br>...
11591  from the recession and the collapsed real esta...
12441  inflation fears on the rise, investors may wan...
14996  on both domestic and foreign policy.</br></br>...
15460  the 1990s, when government spending and taxes ...
```

In [ ]:
```
text_df['length'] = text_df['text'].apply(len)
text_df
```

Out[ ]:

	text	length
0	CEA believe that some special factors, such as...	644
1	approved a $282.6 billion measure to fund the ...	556
2	(AP) ≣ÛÓ An unexpectedly quick rise in. the pr...	453
3	$17.28 million would be put into a reserve for...	469
4	Reserve policy makers voted to keep short-term...	608
...	...	...
15573	Grover Norquist says emphatically and repeated...	423
15574	in die economy, Laura D≣ÛªAndrea Tyson, chairm...	580
15575	of living are not rising noticeably. Many of t...	833
15576	economy merely flexes some long-unused muscles...	767
15577	Video Investments, an investment-research and ...	824

15578 rows × 2 columns

Data Preprocessing

In [ ]:
```
sample = text_df['text'].iloc[12573]
sample
```

Out[ ]:
```
'a recesbave been denied their con-sion or is heading t0wardtitutional ri h
ts by such</br></br>Leading indicators -leavå£nmates 1ft ers and the little
doubt as to which way)Uyn,nfåÈ letters addressed the economy is headed intå
¡ inmates.</br></br>1970\x89ÛÓtoward a recession.\x89Û\x9d Also, it is char
ged that J. Gordon Gifford, editolphotostatic copies of letters of the comm
ission\x89Ûªs monthly inmates have been made report, said all six of th%nd
turned over to the attor-leading indicators were of|,ey general\x89Ûªs offi
ce, in some in January from Decembeijnstances and below the level of Janu-
\t..\t\x89Û_ ary, 1969. He said they had/fhe suit alleges prison of-been de
clining since Septemficials have infringed upon ber.'
```

In [ ]:
```
# Test on a sample text


stemmer = PorterStemmer()
lemmatizer = WordNetLemmatizer()

text = text_df['text'].iloc[12573]

# Remove HTML tags using BeautifulSoup
#clean_text = BeautifulSoup(text).get_text()

#clean_text = ' '.join(re.split(r'<.*?>', clean_text))


clean_text = re.sub("<.*?>",lambda m: " " * len(m.group(0))   , text)
clean_text = ''.join([char for char in text if char not in string.punctuatio


# # Replace specific emojis with corresponding text
# clean_text = re.sub(r'<3', '<heart>' , clean_text)
# clean_text = re.sub(r"[8:=;]['`\-]?[)d]+" , '<smile>' , clean_text)
# clean_text = re.sub(r"[8:=;]['`\-]?\(+" , '<sadface>' , clean_text)
# clean_text = re.sub(r"[8:=;]['`\-]?[\/|l*]" , '<neutralface>' , clean_text
# clean_text = re.sub(r"[8:=;]['`\-]?p+" , '<lolface>' , clean_text)

# # Remove non-alphabetical symbols
clean_text = re.sub('[^A-Za-z ]+', '', clean_text)

# # Remove stopwords
clean_text = ' '.join([word.lower() for word in clean_text.split() if word.l
clean_text = [stemmer.stem(lemmatizer.lemmatize(word.lower())) for word in w

print(clean_text)
```

```
['recesbav', 'deni', 'consion', 'head', 'twardtitut', 'ri', 'ht', 'suchbrbrl
ead', 'indic', 'leavnmat', 'ft', 'er', 'littl', 'doubt', 'wayuynnf', 'lette
r', 'address', 'economi', 'head', 'int', 'inmatesbrbrtoward', 'recess', 'als
o', 'charg', 'j', 'gordon', 'gifford', 'editolphotostat', 'copi', 'letter',
'commiss', 'monthli', 'inmat', 'made', 'report', 'said', 'six', 'thnd', 'tur
n', 'attorlead', 'indic', 'ofey', 'gener', 'offic', 'januari', 'decembeijns
t', 'level', 'janu', 'ari', 'said', 'hadfh', 'suit', 'alleg', 'prison', 'ofb
een', 'declin', 'sinc', 'septemfici', 'infring', 'upon', 'ber']
```

In [ ]:
```
# Create a function
def text_processing(text:str) -> list:

    clean_text = re.sub("<.*?>",lambda m: " " * len(m.group(0))    , text)
    clean_text = ''.join([char for char in clean_text if char not in string.
    clean_text = re.sub("\s+"," ",clean_text)
    clean_text = re.sub('<.*?>',' ',clean_text)
    clean_text = re.sub(r'[^\w ]+', "", clean_text)

    # Convert the text to lowercase for case-insensitive matching
    clean_text_lower = clean_text.lower()

    # Remove non-alphabetical symbols
    clean_text = re.sub('[^A-Za-z ]+', '', clean_text_lower)

    # Remove stopwords
    clean_text = ' '.join([word for word in clean_text.split() if word not i

    # Stem and lemmatize the tokens
    stemmer = LancasterStemmer()
    lemmatizer = WordNetLemmatizer()
    clean_text_tokens = [lemmatizer.lemmatize(stemmer.stem(word)) for word i

    # Define the words and character sequence to check for
    words_to_check = ["economic", "economy", "economics", "econom", "economi

    # Check if any of the words or character sequence are present in the tok
    for word in clean_text_tokens:
        for word_to_check in words_to_check:
            if edit_distance(word, word_to_check) <= 2:
                return clean_text_tokens  # Return the corrected tokens if t

    return clean_text_tokens  # Return the original tokens if none of the wo
```

In [ ]:
```
text_processing(text_df['text'].iloc[5500])
```

```
Out[ ]: ['expect',
         'giv',
         'way',
         'renew',
         'adv',
         'short',
         'turnaround',
         'com',
         'liv',
         'cost',
         'resum',
         'upward',
         'march',
         'exceiv',
         'new',
         'car',
         'pric',
         'exampl',
         'lik',
         'edg',
         'model',
         'rol',
         'produc',
         'lin',
         'deal',
         'custom',
         'shav',
         'pric',
         'model',
         'year',
         'progress',
         'year',
         'poor',
         'sal',
         'perform',
         'enco',
         'many',
         'deal',
         'giv',
         'ev',
         'big',
         'discount',
         'u',
         'word',
         'detroit',
         'model',
         'cost',
         'year',
         'car',
         'mean',
         'automobl',
         'pric',
         'jump',
         'isharply',
         'next',
         'fal']
```

In [ ]:
```python
text_df['tokens'] = text_df['text'].apply(text_processing)
```

In [ ]:
```python
text_df.head()
```

Out[ ]:

	text	length	tokens
0	CEA believe that some special factors, such as...	644	[cea, believ, spec, fact, hug, runup, stock, m...
1	approved a $282.6 billion measure to fund the ...	556	[approv, bil, meas, fund, nat, defens, com, fi...
2	(AP) ≣ÛÓ An unexpectedly quick rise in. the pr...	453	[ap, unexpect, quick, ri, prim, rat, many, nat...
3	$17.28 million would be put into a reserve for...	469	[mil, would, put, reserv, next, year, ev, mone...
4	Reserve policy makers voted to keep short-term...	608	[reserv, policy, mak, vot, keep, shortterm, in...

In [ ]:
```python
# Define a function to check if the specified words or character sequence ar
def check_economic_presence(tokens):
    # Define the words and character sequence to check for
    words_to_check = ["economic", "economy", "economics", "econom", "economi

    # Define the regular expression pattern to search for
    pattern = re.compile(r'econom', re.IGNORECASE)

    # Check if any of the words or character sequence are present in the tok
    for word in tokens:
        if word in words_to_check or pattern.search(word):
            return 1  # Return 1 if any of the words or character sequence a

    return 0  # Return 0 if none of the words or character sequence are four

# Apply the function to the 'tokens' column to create the 'class' column
text_df['class'] = text_df['tokens'].apply(check_economic_presence)
```

In [ ]:
```python
text_df.head(25)
```

Out[ ]:

	text	length	tokens	class
0	CEA believe that some special factors, such as...	644	[cea, believ, spec, fact, hug, runup, stock, m...	1
1	approved a $282.6 billion measure to fund the ...	556	[approv, bil, meas, fund, nat, defens, com, fi...	0
2	(AP) ≣ÛÓ An unexpectedly quick rise in. the pr...	453	[ap, unexpect, quick, ri, prim, rat, many, nat...	0
3	$17.28 million would be put into a reserve for...	469	[mil, would, put, reserv, next, year, ev, mone...	0
4	Reserve policy makers voted to keep short-term...	608	[reserv, policy, mak, vot, keep, shortterm, in...	0
5	the lender asked us if we wanted to lock in.</...	824	[lend, ask, u, want, lock, sint, first, hous, ...	0
6	called off its effort to drive down the value ...	752	[cal, effort, driv, valu, doll, cur, return, a...	1
7	striking unions at. the Greenbrier Hotel resor...	421	[striking, un, greenbry, hotel, resort, whit, ...	0
8	short-term political pressure. But an agency t...	596	[shortterm, polit, press, ag, alloc, credit, s...	0
9	typical recession would drop enough to make st...	797	[typ, recess, would, drop, enough, mak, stock,...	0
10	the standard deduction, personal exemption and...	476	[standard, deduc, person, exempt, cutoff, fig,...	0
11	nation's factories continued to fall last mont...	984	[nat, fact, continu, fal, last, mon, provid, s...	1
12	percentage of those entitled to unemployment i...	971	[perc, entitl, unemploy, in, remain, per, cent...	0
13	the aid earlier than planned threatens to dimi...	1038	[aid, ear, plan, threatens, dimin, impact, lar...	0
14	oversaw the conclusion of his final General As...	729	[oversaw, conclud, fin, gen, assembl, sess, la...	1
15	and labor costs rose sharply in the second qua...	740	[lab, cost, ro, sharply, second, quart, spark,...	0
16	But companies still pay, to the tune of $1.6 b...	540	[company, stil, pay, tun, bil, last, year, pla...	0
17	securities were narrowly mixed in quiet tradin...	618	[sec, narrow, mix, quiet, trad, many, biggest,...	0
18	Japan's real gross domestic product would rise...	212	[jap, real, gross, domest, produc, would, ri, ...	1
19	company. Avon said it was ≣ÛÏnot for sale.≣Û≣<...	371	[company, avon, said, sal, eastm, kodak, drop,...	0

	text	length	tokens	class
20	nearly 18 months, the stock market has been be...	1322	[near, month, stock, market, behav, lik, on, v...	0
21	Maryland continue to decline dramatically, the...	392	[maryland, continu, declin, dram, caseload, pr...	0
22	Cornerstone Financial Partners. </br></br>That ...	584	[cornerston, fin, partn, expect, stok, releas,...	1
23	was a direct attack using the mail as a weapon...	711	[direct, attack, u, mail, weapon, mak, everybo...	0
24	The secretary of defense linked the problem di...	1466	[secret, defens, link, problem, direct, nat, s...	1

```
In [ ]: text_df['tokens'].iloc[1770]
```

```
Out[ ]: ['yearend',
         'predict',
         'econom',
         'forecast',
         'must',
         'struggle',
         'unpleas',
         'real',
         'nobody',
         'thank',
         'correct',
         'predict',
         'bad',
         'new',
         'econom',
         'rosan',
         'cahn',
         'exampl',
         'rememb',
         'od',
         'felt',
         'el',
         'econom',
         'slug',
         'ear',
         'strong',
         'end',
         'happy',
         'predict',
         'slowdown',
         'correct']
```

```
In [ ]: text_df['tokens'].iloc[2192]
```

```
Out[ ]: ['diff',
         'export',
         'importswa',
         'bil',
         'cur',
         'record',
         'deficit',
         'bil',
         'deficit',
         'continu',
         'decemb',
         'rat',
         'first',
         'month',
         'deficit',
         'would',
         'bil',
         'econom',
         'said',
         'yesterday',
         'surpr',
         'enorm',
         'detery',
         'trad',
         'pict',
         'said',
         'increas',
         'deficit',
         'least',
         'part',
         'due',
         'spec',
         'fact',
         'hoard',
         'import',
         'busy',
         'try',
         'beat',
         'elimin',
         'lucr',
         'tax',
         'break',
         'tax',
         'revid',
         'act',
         'went',
         'effect',
         'today',
         'tim',
         'bil',
         'deficit',
         'horrend',
         'on',
         'year',
         'said',
         'commerc',
         'undersecret',
         'robert',
         'ortn',
         'get',
         'accustom',
         'think',
         'horrend',
         'on',
         'mon']
```

In [ ]:
```
sum(text_df['class'])
```

Out[ ]:
```
5266
```

In [ ]:
```
df_class_0 = text_df[text_df['class'] == 0]
```

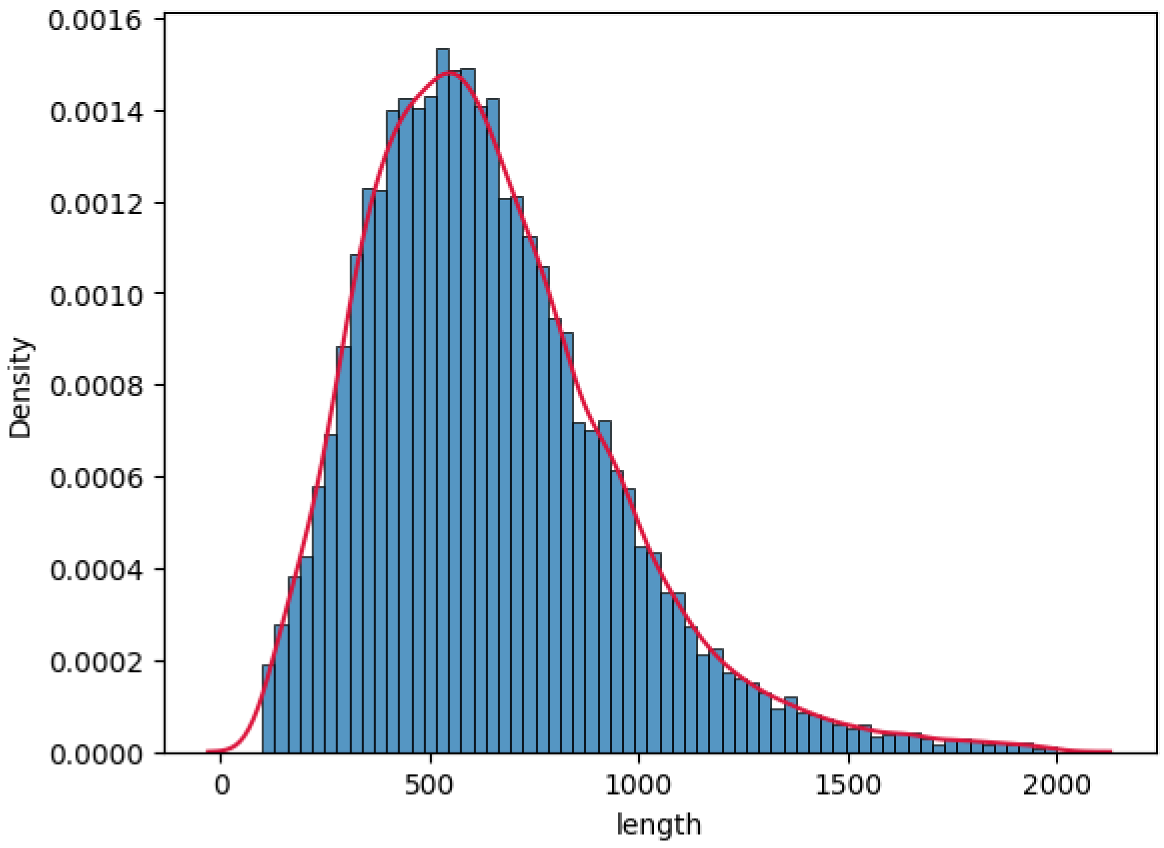
In [ ]:
```
df_class_0['tokens'].head(25)
```

Out[ ]:
```
1      [approv, bil, meas, fund, nat, defens, com, fi...
2      [ap, unexpect, quick, ri, prim, rat, many, nat...
3      [mil, would, put, reserv, next, year, ev, mone...
4      [reserv, policy, mak, vot, keep, shortterm, in...
5      [lend, ask, u, want, lock, sint, first, hous, ...
7      [striking, un, greenbry, hotel, resort, whit, ...
8      [shortterm, polit, press, ag, alloc, credit, s...
9      [typ, recess, would, drop, enough, mak, stock,...
10     [standard, deduc, person, exempt, cutoff, fig,...
12     [perc, entitl, unemploy, in, remain, per, cent...
13     [aid, ear, plan, threatens, dimin, impact, lar...
15     [lab, cost, ro, sharply, second, quart, spark,...
16     [company, stil, pay, tun, bil, last, year, pla...
17     [sec, narrow, mix, quiet, trad, many, biggest,...
19     [company, avon, said, sal, eastm, kodak, drop,...
20     [near, month, stock, market, behav, lik, on, v...
21     [maryland, continu, declin, dram, caseload, pr...
23     [direct, attack, u, mail, weapon, mak, everybo...
25     [mon, fed, most, sharp, increas, grain, pric, ...
26     [recess, already, four, year, spark, gre, soc,...
27     [sharehold, scoreboard, maj, play, industry, s...
29     [int, yesterday, timihc, sel, worthington, dia...
32     [respond, presid, clinton, healthc, propos, bl...
34     [many, expect, increas, risktak, trad, op, cat...
36     [reach, realm, islam, law, just, out, prospect...
Name: tokens, dtype: object
```

Data Visualization

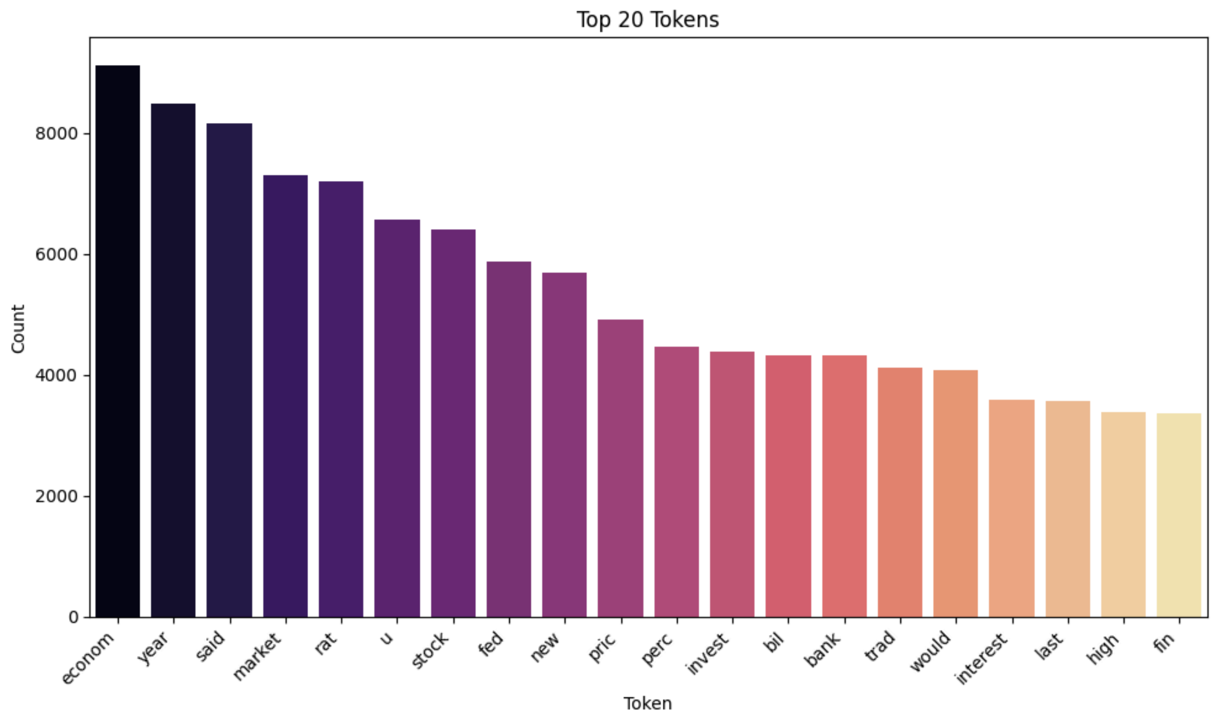
In [ ]:
```
ax = sns.histplot(text_df['length'], kde=False, stat='density' )
sns.kdeplot(text_df['length'], color='crimson', ax=ax)
```

Out[ ]:
```
<Axes: xlabel='length', ylabel='Density'>
```



```
In [ ]: all_tokens = []

        for token_list in text_df['tokens']:
            for word in token_list:
                all_tokens.append(word)

        # Count occurrences of each token
        token_counts = Counter(all_tokens)
        top_words = pd.DataFrame(token_counts.most_common(20), columns = ['word','fr

        print(top_words)
        word  freq
0     econom  9129
1       year  8497
2       said  8166
3     market  7298
4        rat  7193
5          u  6567
6      stock  6399
7        fed  5866
8        new  5689
9       pric  4922
10      perc  4456
11    invest  4379
12       bil  4322
13      bank  4314
14      trad  4128
15     would  4088
16  interest  3594
17      last  3577
18      high  3388
19       fin  3371
```

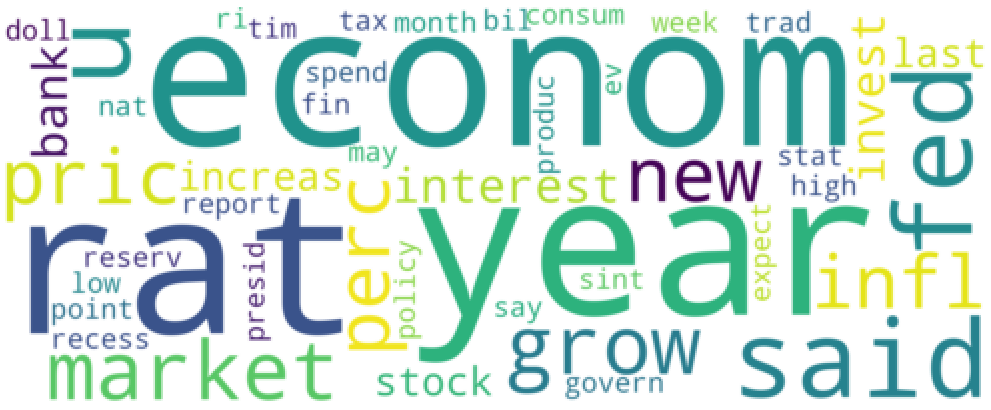
In [ ]:
```python
top_tokens = dict(token_counts.most_common(20))
# Plot the top 20 tokens
plt.figure(figsize=(10, 6))
ax = sns.barplot(top_words, x = 'word' , y='freq' , palette='magma')
plt.xlabel('Token')
plt.ylabel('Count')
plt.title('Top 20 Tokens')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



```
In [ ]: all_econ_tokens = []

        econ_df = text_df.loc[text_df['class'] == 1]

        for token_list in econ_df['tokens']:
            for word in token_list:
                all_econ_tokens.append(word)

        # Count occurrences of each token
        econ_token_counts = Counter(all_econ_tokens)

        top_econ_tokens_tup = econ_token_counts.most_common(50)

        top_econ_tokens_list = [token for token, _ in econ_token_counts.most_common(

        # Print the top 50 tokens and their counts
        for token, count in econ_token_counts.most_common(50):
            print(f"{token}: {count}")
```

```
econom: 9129
rat: 3630
year: 3338
said: 3234
u: 2896
fed: 2867
market: 2384
grow: 2177
pric: 2024
new: 1917
perc: 1893
infl: 1760
interest: 1601
would: 1562
bank: 1528
invest: 1497
increas: 1450
stock: 1446
last: 1377
report: 1338
high: 1334
trad: 1245
bil: 1240
fin: 1238
nat: 1228
govern: 1201
week: 1157
stat: 1154
presid: 1125
low: 1118
tax: 1103
expect: 1084
off: 1035
produc: 1017
doll: 1007
ev: 1006
ri: 1005
say: 999
recess: 986
reserv: 985
point: 970
consum: 960
month: 960
policy: 958
tim: 950
on: 935
may: 933
could: 933
spend: 927
sint: 918
```

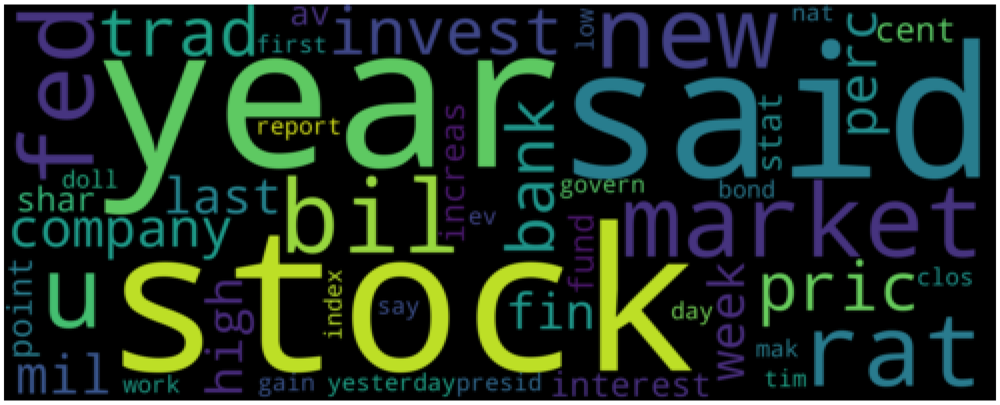
In [ ]:
```
def word_cloud(tokens):
    #Creation of wordcloud
    wordcloud = WordCloud(
        max_font_size=100,
        max_words=50,
        background_color="white",
        scale=10,
        width=500,
        height=200
    ).generate(" ".join(top_econ_tokens_list))
    #Figure properties
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis("off")
    plt.show()

word_cloud(top_econ_tokens_list)
```



```
In [ ]: all_nonecon_tokens = []

        nonecon_df = text_df.loc[text_df['class'] == 0]

        for token_list in nonecon_df['tokens']:
            for word in token_list:
                all_nonecon_tokens.append(word)

        # Count occurrences of each token
        nonecon_token_counts = Counter(all_nonecon_tokens)

        top_nonecon_tokens_tup = nonecon_token_counts.most_common(50)

        top_nonecon_tokens_list = [token for token, _ in nonecon_token_counts.most_c

        # Print the top 50 tokens and their counts
        for token, count in nonecon_token_counts.most_common(50):
            print(f"{token}: {count}")
```

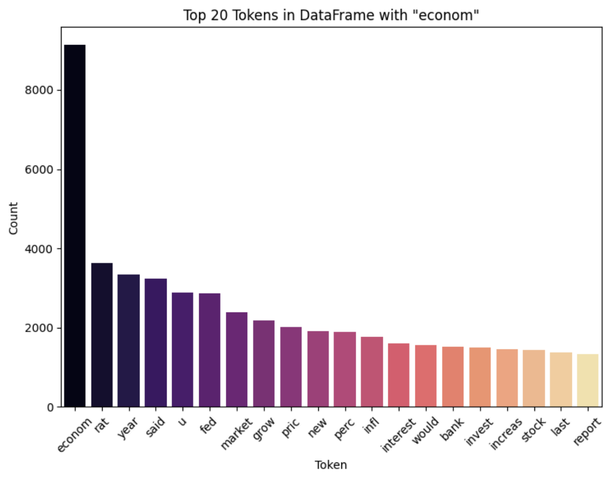
```
year: 5159
stock: 4953
said: 4932
market: 4914
new: 3772
u: 3671
rat: 3563
bil: 3082
fed: 2999
pric: 2898
trad: 2883
invest: 2882
bank: 2786
company: 2694
mil: 2668
perc: 2563
would: 2526
off: 2242
last: 2200
week: 2145
fin: 2133
high: 2054
interest: 1993
point: 1939
increas: 1892
shar: 1865
on: 1834
stat: 1797
cent: 1749
av: 1745
fund: 1700
yesterday: 1575
govern: 1571
report: 1566
tim: 1540
work: 1537
say: 1527
presid: 1480
day: 1467
mak: 1457
nat: 1456
first: 1450
bond: 1444
clos: 1436
low: 1425
index: 1411
doll: 1408
gain: 1403
also: 1397
ev: 1384
```

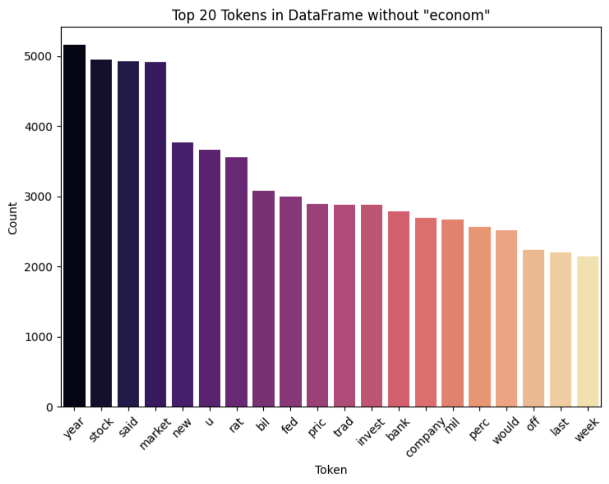
In [ ]:
```
def word_cloud(tokens):
    #Creation of wordcloud
    wordcloud = WordCloud(
        max_font_size=100,
        max_words=50,
        background_color="black",
        scale=10,
        width=500,
        height=200
    ).generate(" ".join(top_nonecon_tokens_list))
    #Figure properties
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis("off")
    plt.show()

word_cloud(top_nonecon_tokens_list)
```



In [ ]:
```
top_econ_words_df = pd.DataFrame(econ_token_counts.most_common(20), columns

top_nonecon_words_df = pd.DataFrame(nonecon_token_counts.most_common(20), co
```

In [ ]:
```
# Create subplots
fig, axs = plt.subplots(1, 2, figsize=(15, 6))

# Plot top tokens in DataFrame with 'econom'
sns.barplot(data=top_econ_words_df, x='word', y='freq', ax=axs[0], palette='
axs[0].set_title('Top 20 Tokens in DataFrame with "econom"')
axs[0].set_xlabel('Token')
axs[0].set_ylabel('Count')
axs[0].tick_params(axis='x', labelrotation=45)

# Plot top tokens in DataFrame without 'econom'
sns.barplot(data=top_nonecon_words_df, x='word', y='freq', ax=axs[1], palett
axs[1].set_title('Top 20 Tokens in DataFrame without "econom"')
axs[1].set_xlabel('Token')
axs[1].set_ylabel('Count')
axs[1].tick_params(axis='x', labelrotation=45)

# Adjust layout
plt.tight_layout()

# Show plot
plt.show()
```





Neural Network

Splitting and transforming the data

```
In [ ]: X_train, X_test, y_train, y_test = train_test_split(text_df[['text']], text_
```

```
In [ ]: bow_transformer = CountVectorizer(analyzer=text_processing).fit(X_train['tex
```

```
In [ ]: X_train_bow = bow_transformer.transform(X_train['text'])
        X_test_bow = bow_transformer.transform(X_test['text'])
```

```
In [ ]: print('Shape of Sparse Matrix: ', X_train_bow.shape, X_test_bow.shape)
        print('Amount of Non-Zero occurences: ', X_train_bow.nnz,  X_test_bow.nnz)
```

```
Shape of Sparse Matrix:  (10904, 23875) (4674, 23875)
Amount of Non-Zero occurences:  537100 226174
```

```
In [ ]: max_abs_scaler = preprocessing.MaxAbsScaler()
```

```
In [ ]: # max_abs_scaler.fit(X_train_bow)
        # # transform
        # X_train_bow_scaled = max_abs_scaler.transform(X_train_bow)
        # X_test_bow_scaled = max_abs_scaler.transform(X_test_bow)
```

```
In [ ]: X_train_bow_scaled_array = X_train_bow.toarray()
        X_test_bow_scaled_array = X_test_bow.toarray()
        #X_train_tfidf_array = X_train_tfidf.toarray()
```

```
In [ ]: from sklearn.feature_extraction.text import TfidfTransformer
        tfidf_transformer = TfidfTransformer().fit(X_train_bow)
```

```
In [ ]: X_train_tfidf = tfidf_transformer.transform(X_train_bow)
        X_test_tfidf = tfidf_transformer.transform(X_test_bow)
```

```
In [ ]: X_train_tfidf_array = X_train_tfidf.toarray()
        X_test_tfidf_array = X_test_tfidf.toarray()
```

In [ ]:
```
X_train_bow_scaled_array.shape
```
Out[ ]:
```
(10904, 23875)
```
In [ ]:
```
y_train.shape
```
Out[ ]:
```
(10904,)
```
In [ ]:
```
y_train_categorical = to_categorical(y_train, num_classes=2)
y_test_categorical = to_categorical(y_test, num_classes=2)
```
In [ ]:
```
y_train_categorical.shape
```
Out[ ]:
```
(10904, 2)
```
In [ ]:
```
from tensorflow.keras.layers import BatchNormalization

nrows, nfeat = X_test_tfidf.shape

model = Sequential()
model.add(Input(shape=(nfeat,)))
model.add(BatchNormalization())
model.add(Dense(50, activation='relu'))
model.add(Dense(50, activation='relu'))
model.add(Dense(2, activation='softmax'))
model.summary()
```
Model: "sequential_3"

Layer (type)	Output Shape	Par
batch_normalization_1 (BatchNormalization)	(None, 23875)	95
dense_8 (Dense)	(None, 50)	1,193
dense_9 (Dense)	(None, 50)	2
dense_10 (Dense)	(None, 2)	

Total params: 1,291,952 (4.93 MB)

Trainable params: 1,244,202 (4.75 MB)

Non-trainable params: 47,750 (186.52 KB)

In [ ]:
```
#optimizer = tf.keras.optimizers.legacy.Adam(learning_rate=0.001)
model.compile(loss="binary_crossentropy",
              optimizer='adam',
              metrics=['accuracy'])
```
In [ ]:
```
model_history = model.fit(X_train_tfidf_array, y_train_categorical, epochs=5
                          validation_split=.3,
                          batch_size=64
                          )
```

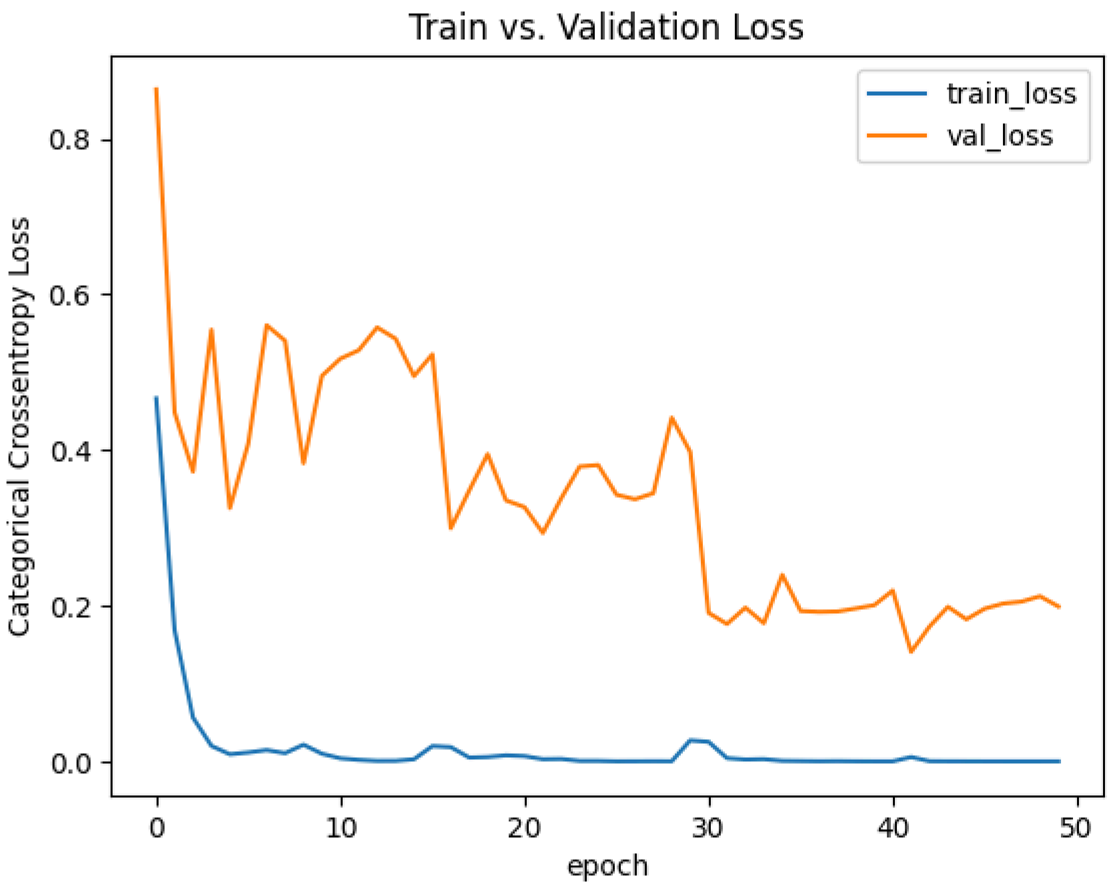
```
Epoch 1/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 2s 16ms/step - accuracy: 0.7152 - loss: 0.5345
- val_accuracy: 0.6537 - val_loss: 0.8633
Epoch 2/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9251 - loss: 0.1832
- val_accuracy: 0.8817 - val_loss: 0.4484
Epoch 3/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9802 - loss: 0.0676
- val_accuracy: 0.8322 - val_loss: 0.3722
Epoch 4/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9946 - loss: 0.0197
- val_accuracy: 0.8295 - val_loss: 0.5545
Epoch 5/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9990 - loss: 0.0069
- val_accuracy: 0.8884 - val_loss: 0.3254
Epoch 6/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9983 - loss: 0.0065
- val_accuracy: 0.8854 - val_loss: 0.4085
Epoch 7/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9957 - loss: 0.0175
- val_accuracy: 0.8848 - val_loss: 0.5603
Epoch 8/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9974 - loss: 0.0078
- val_accuracy: 0.8640 - val_loss: 0.5404
Epoch 9/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9921 - loss: 0.0251
- val_accuracy: 0.8933 - val_loss: 0.3830
Epoch 10/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9958 - loss: 0.0164
- val_accuracy: 0.8927 - val_loss: 0.4953
Epoch 11/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9990 - loss: 0.0036
- val_accuracy: 0.8933 - val_loss: 0.5173
Epoch 12/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9987 - loss: 0.0030
- val_accuracy: 0.8955 - val_loss: 0.5282
Epoch 13/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 1.0000 - loss: 8.8914e
-04 - val_accuracy: 0.8973 - val_loss: 0.5575
Epoch 14/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9997 - loss: 8.1162e
-04 - val_accuracy: 0.9007 - val_loss: 0.5430
Epoch 15/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - accuracy: 0.9997 - loss: 0.0012
- val_accuracy: 0.8961 - val_loss: 0.4950
Epoch 16/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9955 - loss: 0.0136
- val_accuracy: 0.9089 - val_loss: 0.5229
Epoch 17/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9936 - loss: 0.0182
- val_accuracy: 0.9163 - val_loss: 0.2994
Epoch 18/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9979 - loss: 0.0051
- val_accuracy: 0.9224 - val_loss: 0.3480
Epoch 19/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9994 - loss: 0.0020
```

```
- val_accuracy: 0.9215 - val_loss: 0.3947
Epoch 20/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9976 - loss: 0.0071
- val_accuracy: 0.9282 - val_loss: 0.3352
Epoch 21/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9987 - loss: 0.0072
- val_accuracy: 0.9294 - val_loss: 0.3267
Epoch 22/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - accuracy: 0.9991 - loss: 0.0020
- val_accuracy: 0.9325 - val_loss: 0.2934
Epoch 23/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9983 - loss: 0.0051
- val_accuracy: 0.9334 - val_loss: 0.3381
Epoch 24/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9999 - loss: 4.8839e
-04 - val_accuracy: 0.9334 - val_loss: 0.3788
Epoch 25/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - accuracy: 0.9996 - loss: 0.0010
- val_accuracy: 0.9370 - val_loss: 0.3807
Epoch 26/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 1.0000 - loss: 7.9415e
-05 - val_accuracy: 0.9383 - val_loss: 0.3425
Epoch 27/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 1.0000 - loss: 1.1598e
-04 - val_accuracy: 0.9389 - val_loss: 0.3367
Epoch 28/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9999 - loss: 1.4333e
-04 - val_accuracy: 0.9401 - val_loss: 0.3445
Epoch 29/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 1.0000 - loss: 3.4319e
-05 - val_accuracy: 0.9325 - val_loss: 0.4415
Epoch 30/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9903 - loss: 0.0282
- val_accuracy: 0.9322 - val_loss: 0.3975
Epoch 31/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9856 - loss: 0.0457
- val_accuracy: 0.9535 - val_loss: 0.1908
Epoch 32/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9992 - loss: 0.0024
- val_accuracy: 0.9557 - val_loss: 0.1765
Epoch 33/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9991 - loss: 0.0029
- val_accuracy: 0.9575 - val_loss: 0.1974
Epoch 34/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9984 - loss: 0.0041
- val_accuracy: 0.9578 - val_loss: 0.1775
Epoch 35/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 1.0000 - loss: 7.9538e
-04 - val_accuracy: 0.9545 - val_loss: 0.2396
Epoch 36/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9999 - loss: 3.7480e
-04 - val_accuracy: 0.9578 - val_loss: 0.1932
Epoch 37/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 1.0000 - loss: 1.8499e
-04 - val_accuracy: 0.9584 - val_loss: 0.1921
Epoch 38/50
```

```
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9999 - loss: 2.4668e
-04 - val_accuracy: 0.9584 - val_loss: 0.1925
Epoch 39/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 1.0000 - loss: 1.0866e
-04 - val_accuracy: 0.9587 - val_loss: 0.1965
Epoch 40/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 1.0000 - loss: 3.5893e
-05 - val_accuracy: 0.9587 - val_loss: 0.2007
Epoch 41/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 1.0000 - loss: 2.7653e
-05 - val_accuracy: 0.9578 - val_loss: 0.2194
Epoch 42/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9987 - loss: 0.0034
- val_accuracy: 0.9572 - val_loss: 0.1407
Epoch 43/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 1.0000 - loss: 3.5677e
-04 - val_accuracy: 0.9575 - val_loss: 0.1733
Epoch 44/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 1.0000 - loss: 1.0776e
-04 - val_accuracy: 0.9575 - val_loss: 0.1986
Epoch 45/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 1.0000 - loss: 4.1310e
-05 - val_accuracy: 0.9584 - val_loss: 0.1825
Epoch 46/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - accuracy: 1.0000 - loss: 5.3241e
-05 - val_accuracy: 0.9578 - val_loss: 0.1962
Epoch 47/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 1.0000 - loss: 2.3470e
-05 - val_accuracy: 0.9587 - val_loss: 0.2028
Epoch 48/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 1.0000 - loss: 1.2902e
-05 - val_accuracy: 0.9587 - val_loss: 0.2052
Epoch 49/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 1.0000 - loss: 3.0316e
-05 - val_accuracy: 0.9590 - val_loss: 0.2121
Epoch 50/50
120/120 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 1.0000 - loss: 4.9945e
-05 - val_accuracy: 0.9597 - val_loss: 0.1989
```

In [ ]:

```
plt.plot(model_history.history['loss'], label='train_loss')
plt.plot(model_history.history['val_loss'], label='val_loss')
plt.legend()
plt.title('Train vs. Validation Loss')
plt.xlabel('epoch')
plt.ylabel('Categorical Crossentropy Loss')
plt.show()
```



In [ ]:
```
# Make predictions using your trained neural network
nn_y_pred = model.predict(X_test_tfidf_array)

# Define an initial threshold
threshold = 0.5

# Calculate the proportion of predicted 1s
proportion_1s = np.mean(nn_y_pred[:, 1])

# Adjust the threshold based on the proportion of 1s
if proportion_1s > 0.5:
    threshold -= 0.05  # Decrease the threshold if there are too many 1s
else:
    threshold += 0.05  # Increase the threshold if there are too few 1s

# Threshold the probabilities to get the predicted classes
y_pred_int = (nn_y_pred[:, 1] > threshold).astype(int)

# Now you can evaluate the predictions as usual
```

```
147/147 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
```

In [ ]:
```
len(y_pred_int)
```

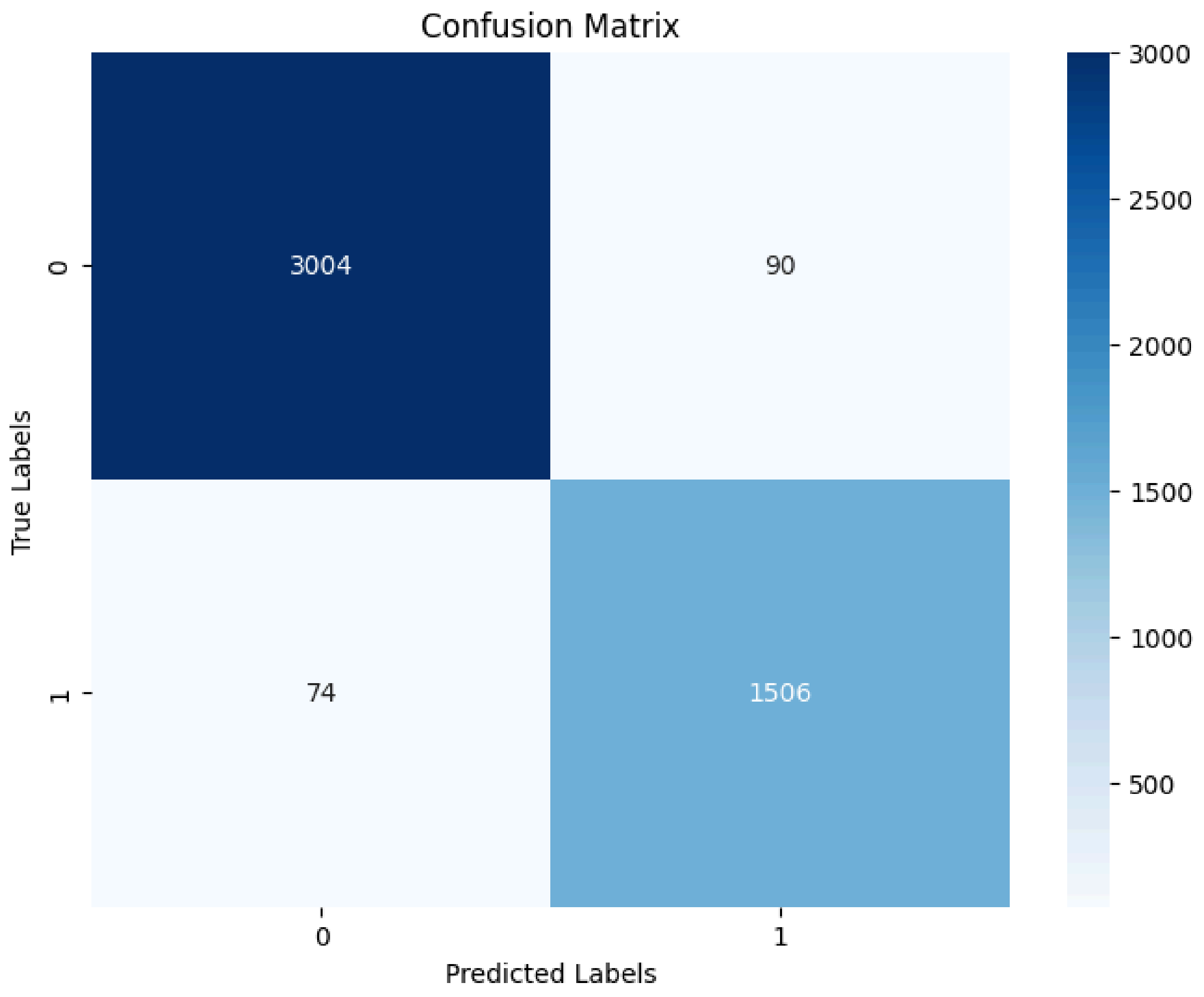
Out[ ]:
```
4674
```

In [ ]:
```
# y_pred_int = np.argmax(nn_y_pred, axis=1)
```

In [ ]:
```python
report = classification_report(y_test, y_pred_int)
print("Classification Report:\n", report)
```

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

           0       0.98      0.97      0.97      3094
           1       0.94      0.95      0.95      1580

    accuracy                           0.96      4674
   macro avg       0.96      0.96      0.96      4674
weighted avg       0.97      0.96      0.96      4674
```

In [ ]:
```python
cm = confusion_matrix(y_test, y_pred_int)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, cmap='Blues', fmt='d')
plt.title("Confusion Matrix")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.show()
```



In [ ]:
```python
y_pred_int
```

```
Out[ ]:  array([0, 0, 1, ..., 1, 0, 1])
```

```
In [ ]:  text_bow_transformer = CountVectorizer(analyzer=text_processing).fit(text_df
```

```
In [ ]:  text_bow = bow_transformer.transform(text_df['text'])
```

```
In [ ]:  max_abs_scaler.fit(text_bow)

         # text_bow_scaled = max_abs_scaler.transform(text_bow)
```

```
Out[ ]:  ▾ MaxAbsScaler
         MaxAbsScaler()
```

```
In [ ]:  text_tfidf_transformer = TfidfTransformer().fit(text_bow)
```

```
In [ ]:  text_tfidf = tfidf_transformer.transform(text_bow)
```

```
In [ ]:  text_tfidf_array = text_tfidf.toarray()
```

```
In [ ]:  nn_class_pred = model.predict(text_tfidf_array)
         487/487 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```

```
In [ ]:  len(nn_class_pred)
```

```
Out[ ]:  15578
```

```
In [ ]:  # Calculate the predictions based on the threshold directly from nn_class_pr
         prediction_unseen_classes = [1 if prob[1] > 0.00000000000672 else 0 for prob

         # No need to use np.ravel() here
```

```
In [ ]:  len(prediction_unseen_classes)
```

```
Out[ ]:  15578
```

```
In [ ]:  class_pred_int = np.argmax(nn_class_pred, axis=1)
```

```
In [ ]:  text_df['predictions'] = prediction_unseen_classes
```

```
In [ ]:  sum(text_df['predictions'])
```

```
Out[ ]:  7765
```

```
In [ ]:  import pandas as pd

         # Assuming text_df is your DataFrame
         filtered_df = text_df[(text_df['class'] == 1) & (text_df['predictions'] == 0
         # Display the filtered DataFrame
         print(filtered_df)
```

```
                                                    text  length  \
569    stocks rose slightly today and the ; broader m...     501   
1072   BEACH, Fin., Feb. 15ÛÓIf thereÛªs a recessio...     722   
2617   to offset the reported deficit, but said the m...     571   
2795   are completely burned. Only odorless vapors es...    1251   
3438   of companies doing business in South Africa do...     819   
3642   Columd high level positions in local bia Commi...     970   
4332   offering low prices. The legislation's support...    1799   
5838   funds, index funds received about 25 percent o...     575   
9214   at the three leading U.S. auto executives yest...     734   
9929   Ways and Means Committee will introduce its ec...     723   
11141  to lending to low- and moderate-income groups....     678   
12362  from secretaries' salaries to research -- what...     826   
14348  falling to C$141 million from C$323 million.</...     331   
14630  have been introduced in the Senate. Here's a c...     394   

                                                  tokens  class  predictions  
569    [stock, ro, slight, today, broad, market, mix,...      1            0  
1072   [beach, fin, feb, ther, recess, yet, com, litt...      1            0  
2617   [offset, report, deficit, said, money, repres,...      1            0  
2795   [complet, burn, odorless, vap, escap, flu, aft...      1            0  
3438   [company, busy, sou, afric, doesnt, seem, driv...      1            0  
3642   [columd, high, level, posit, loc, bia, commit,...      1            0  
4332   [off, low, pric, legisl, support, said, new, l...      1            0  
5838   [fund, index, fund, receiv, perc, inflow, deva...      1            0  
9214   [three, lead, u, auto, execut, yesterday, figh...      1            0  
9929   [way, mean, commit, introduc, economicstimul, ...      1            0  
11141  [lend, low, moderateincom, group, stil, acquis...      1            0  
12362  [secret, sal, research, known, budget, jargon,...      1            0  
14348  [fal, c, mil, c, mil, stil, bmo, remain, optim...      1            0  
14630  [introduc, sen, her, comparison, provid, econo...      1            0  
```

In [ ]:
```
# Assuming text_df is your DataFrame
text_df.loc[(text_df['class'] == 1) & (text_df['predictions'] == 0), 'predic
```

In [ ]:
```
sum(text_df['predictions'])
```

Out[ ]:
```
7779
```

In [ ]:
```
preds = text_df['predictions']

predictions_df = pd.DataFrame({'predictions': preds})

header = pd.DataFrame({
    'predictions': [21108082, 'KentoNanami']
})

header

output_df = pd.concat([header, predictions_df], axis=0)

# Specify the path where you want to save the CSV file
output_csv_path = "/Users/andrew/Downloads/UW courses/ECON 626/Prediction Co
```

```
# Write the combined DataFrame to a CSV file
output_df.to_csv(output_csv_path, index=False, header=False)
```

In [ ]:
```
preds
```

Out[ ]:
```
0        1
1        0
2        1
3        0
4        1
        ..
15573    1
15574    1
15575    1
15576    1
15577    1
Name: predictions, Length: 15578, dtype: int64
```

In [ ]: