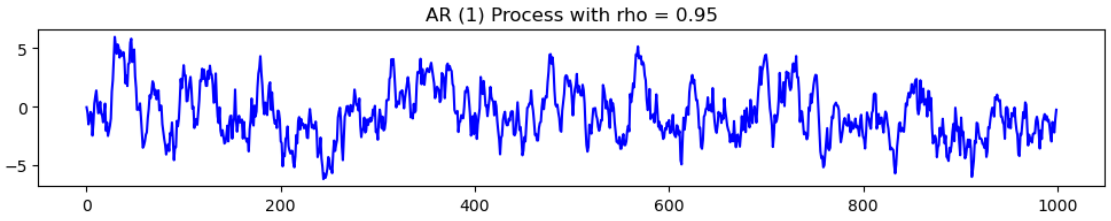
3. Additional coding for the research

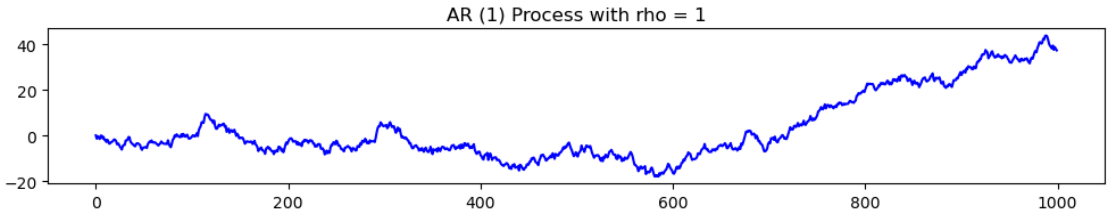
May 21, 2023

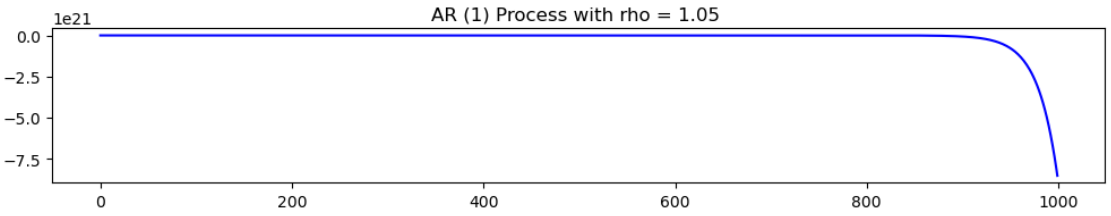
1 AR(1) - Process

[1]:
```
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.arima_process import ArmaProcess

plt.figure(figsize=(12, 6))


# Plot 1: AR parameter = +0.9
plt.subplot(3,1,1)
ar1 = np.array([1, -0.9])
ma1 = np.array([1])
AR_object1 = ArmaProcess(ar1, ma1)
simulated_data_1 = AR_object1.generate_sample(nsample=1000)
plt.title("AR (1) Process with rho = 0.95")
plt.plot(simulated_data_1, color='blue')

#-------------------------------------------------------------------------------------------

# Plot 2: AR parameter = 1
plt.figure(figsize=(12, 6))

plt.subplot(3,1,2)
ar2 = np.array([1, -1])
ma2 = np.array([1])
AR_object2 = ArmaProcess(ar2, ma2)
simulated_data_2 = AR_object2.generate_sample(nsample=1000)
plt.title("AR (1) Process with rho = 1")
plt.plot(simulated_data_2, color='blue')
plt.show()

#-------------------------------------------------------------------------------------------
# Plot 3: AR parameter = 1.05
plt.figure(figsize=(12, 6))

plt.subplot(3,1,3)
```

```
ar3 = np.array([1, -1.05])
ma3 = np.array([1])
AR_object3 = ArmaProcess(ar3, ma3)
simulated_data_3 = AR_object3.generate_sample(nsample=1000)
plt.title("AR (1) Process with rho = 1.05 ")
plt.plot(simulated_data_3, color='blue')
plt.show()
```







2 NLP: Sentiment Analysis

1. ref: https://pythonkai.org/2022/01/23/sentiment-analysis-on-50-000-bitcoin-tweets/

[1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import datetime
from datetime import datetime
import dateutil.relativedelta
```

```
import eikon as ek
ek.set_app_key('XYZ')

#NLP
from nltk.tokenize import word_tokenize, sent_tokenize
from nltk.sentiment.vader import SentimentIntensityAnalyzer
import nltk
```

[11]:
```
now = datetime.now()
maxenddate = now - dateutil.relativedelta.relativedelta(years=10) #months,days
print(now, maxenddate)
```

```
2023-04-12 17:50:38.388840 2013-04-12 17:50:38.388840
```

[12]:
```
newsdf = pd.DataFrame()
startdf=now
while startdf >= maxenddate:
    try:
        df1 = ek.get_news_headlines('BTC= AND Language:EN', date_to = startdf,␣
 ↪count=100)
        startdf = df1['versionCreated'].min().
 ↪replace(second=0,microsecond=0,tzinfo=None).strftime('%Y/%m/%d %H:%M')
        startdf = datetime.strptime(startdf,'%Y/%m/%d %H:%M')
        if len(newsdf):
            newsdf = pd.concat([newsdf, df1], axis=0)
        else:
            newsdf = df1
    except Exception:
        break
```

[13]:
```
newsdf
```

[13]:
```
                                          versionCreated  \
2023-04-12 15:28:28.901 2023-04-12 15:28:28.901000+00:00
2023-04-12 15:28:28.884 2023-04-12 15:28:28.884000+00:00
2023-04-12 15:08:01.000        2023-04-12 15:08:01+00:00
2023-04-12 14:49:52.109 2023-04-12 14:55:27.509000+00:00
2023-04-12 14:55:15.585 2023-04-12 14:55:15.585000+00:00
…                                                      …
2022-01-12 18:52:47.000        2022-01-12 18:52:47+00:00
2022-01-12 18:20:51.000        2022-01-12 18:20:51+00:00
2022-01-12 17:26:25.926 2022-01-12 17:26:25.926000+00:00
2022-01-12 16:20:40.000        2022-01-12 16:20:40+00:00
2022-01-12 16:08:35.000        2022-01-12 16:08:35+00:00

                                                                    text  \
2023-04-12 15:28:28.901      First Mover Americas: Ether's Shanghai Rumble
2023-04-12 15:28:28.884  Argentina’s National Securities Commission App…
```

```
2023-04-12 15:08:01.000  LIVE MARKETS-Inflation follies: CPI cools, but…
2023-04-12 14:49:52.109  Refinitiv Newscasts - Bitcoin Remains Above $3…
2023-04-12 14:55:15.585    Warren Buffett Calls Bitcoin a 'Gambling Token'
…                                                                      …
2022-01-12 18:52:47.000  LIVE MARKETS-Don't move your eggs from the U.S…
2022-01-12 18:20:51.000     LIVE MARKETS-How to play the Fed with sectors
2022-01-12 17:26:25.926    Does crypto allocation enhance your portfolio?
2022-01-12 16:20:40.000  LIVE MARKETS-Bond markets: doing one's homewor…
2022-01-12 16:08:35.000  BUZZ-BTCS more than doubles since announcing b…

                                                                storyId  \
2023-04-12 15:28:28.901  urn:newsml:newswire.refinitiv.com:20230412:nCD…
2023-04-12 15:28:28.884  urn:newsml:newswire.refinitiv.com:20230412:nCD…
2023-04-12 15:08:01.000  urn:newsml:newswire.refinitiv.com:20230412:nL1…
2023-04-12 14:49:52.109  urn:newsml:newswire.refinitiv.com:20230412:nRT…
2023-04-12 14:55:15.585  urn:newsml:newswire.refinitiv.com:20230412:nCD…
…                                                                      …
2022-01-12 18:52:47.000  urn:newsml:newswire.refinitiv.com:20220112:nL1…
2022-01-12 18:20:51.000  urn:newsml:newswire.refinitiv.com:20220112:nL1…
2022-01-12 17:26:25.926  urn:newsml:newswire.refinitiv.com:20220112:nNR…
2022-01-12 16:20:40.000  urn:newsml:newswire.refinitiv.com:20220112:nL1…
2022-01-12 16:08:35.000  urn:newsml:newswire.refinitiv.com:20220112:nL4…

                        sourceCode
2023-04-12 15:28:28.901    NS:COIN
2023-04-12 15:28:28.884    NS:COIN
2023-04-12 15:08:01.000    NS:RTRS
2023-04-12 14:49:52.109    NS:COIN
2023-04-12 14:55:15.585    NS:COIN
…                             …
2022-01-12 18:52:47.000    NS:RTRS
2022-01-12 18:20:51.000    NS:RTRS
2022-01-12 17:26:25.926  NS:MINTNE
2022-01-12 16:20:40.000    NS:RTRS
2022-01-12 16:08:35.000    NS:RTRS

[6224 rows x 4 columns]
```

[14]:
```
btc = ek.get_timeseries(['BTC='], start_date = '2013-03-12T09:00:00', end_date␣
↪= '2023-03-06')
btc_news = ek.get_news_headlines('BTC=',count = 100)
btc_news = pd.DataFrame(btc_news['text'])
```

[15]:
```
newsdf_t = newsdf['text']
newsdf_t = pd.DataFrame(newsdf_t)
```

[16]:
```
sia = SentimentIntensityAnalyzer()

# we use the apply function to apply the polarity_scores function to each row␣
 ↪of the 'text' column
newsdf['sentiment_scores'] = newsdf['text'].apply(sia.polarity_scores)

# Extract each sentiment score into separate columns
newsdf[['pos', 'neg', 'neu', 'compound']] = newsdf['sentiment_scores'].apply(pd.
 ↪Series)
```

[17]:
```
sia = SentimentIntensityAnalyzer()

# Use the apply function to apply the polarity_scores function to each row of␣
 ↪the 'text' column
newsdf['sentiment_scores'] = newsdf['text'].apply(sia.polarity_scores)

# Extract each sentiment score into separate columns
newsdf[['pos', 'neg', 'neu', 'compound']] = newsdf['sentiment_scores'].apply(pd.
 ↪Series)

# Resample the DataFrame and calculate the mean sentiment scores for each day
daily_sentiment = newsdf.resample('D')[['pos', 'neg', 'neu', 'compound']].mean()

# Reset the index to make the day a regular column
daily_sentiment.reset_index(inplace=True)
daily_sentiment = daily_sentiment.dropna()

print(daily_sentiment)
```

```
         index       pos       neg       neu  compound
0   2022-01-12  0.025667  0.831000  0.143333  0.103867
1   2022-01-13  0.130500  0.822300  0.047200 -0.131450
2   2022-01-14  0.110400  0.775800  0.113800 -0.017550
3   2022-01-15  0.000000  1.000000  0.000000  0.000000
4   2022-01-16  0.000000  0.617000  0.383000  0.476700
..         …       …         …         …         …
451 2023-04-08  0.068667  0.931333  0.000000 -0.127267
452 2023-04-09  0.000000  1.000000  0.000000  0.000000
453 2023-04-10  0.157667  0.800333  0.042000 -0.176617
454 2023-04-11  0.034258  0.891045  0.074697  0.063267
455 2023-04-12  0.049969  0.847375  0.102656  0.077934

[438 rows x 5 columns]
```

[18]:
```
newsdf['text']
```

[18]:
```
2023-04-12 15:28:28.901        First Mover Americas: Ether's Shanghai Rumble
2023-04-12 15:28:28.884    Argentina's National Securities Commission App…
2023-04-12 15:08:01.000    LIVE MARKETS-Inflation follies: CPI cools, but…
2023-04-12 14:49:52.109    Refinitiv Newscasts - Bitcoin Remains Above $3…
2023-04-12 14:55:15.585      Warren Buffett Calls Bitcoin a 'Gambling Token'
                                                    …
2022-01-12 18:52:47.000    LIVE MARKETS-Don't move your eggs from the U.S…
2022-01-12 18:20:51.000        LIVE MARKETS-How to play the Fed with sectors
2022-01-12 17:26:25.926       Does crypto allocation enhance your portfolio?
2022-01-12 16:20:40.000    LIVE MARKETS-Bond markets: doing one's homewor…
2022-01-12 16:08:35.000    BUZZ-BTCS more than doubles since announcing b…
Name: text, Length: 6224, dtype: string
```

The compound score ranges from -1 to 1:

```
A compound score close to -1 indicates a highly negative sentiment.
A compound score close to 1 indicates a highly positive sentiment.
A compound score close to 0 indicates a neutral or mixed sentiment.
```

Positive (pos): This score indicates the proportion of positive sentiment in the text. It ranges from 0 to 1, where higher values represent a higher proportion of positive sentiment. A text with a high positive score contains a significant number of positive words or phrases.

Negative (neg): This score indicates the proportion of negative sentiment in the text. It also ranges from 0 to 1, where higher values represent a higher proportion of negative sentiment. A text with a high negative score contains a significant number of negative words or phrases.

Neutral (neu): This score indicates the proportion of neutral sentiment in the text. It ranges from 0 to 1, where higher values represent a higher proportion of neutral sentiment. A text with a high neutral score contains a significant number of neutral words or phrases, or it may contain an even mix of positive and negative words, making the overall sentiment neutral.

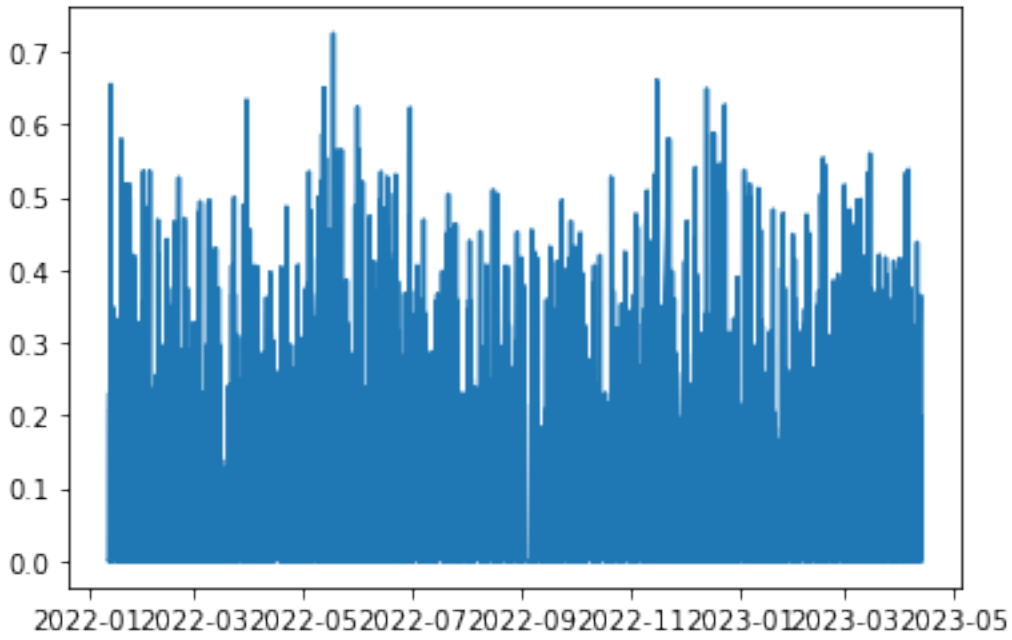
[19]:
```python
# Access the sentiment scores
positive_scores = newsdf['pos']
negative_scores = newsdf['neg']
neutral_scores = newsdf['neu']
compound_scores = newsdf['compound']

# Calculate the average sentiment scores
avg_positive = positive_scores.mean()
avg_negative = negative_scores.mean()
avg_neutral = neutral_scores.mean()
avg_compound = compound_scores.mean()

print("Average Positive Sentiment Score:", avg_positive)
print("Average Negative Sentiment Score:", avg_negative)
print("Average Neutral Sentiment Score:", avg_neutral)
print("Average Compound Sentiment Score:", avg_compound)
```

```
Average Positive Sentiment Score: 0.08146850899742933
```

```
Average Negative Sentiment Score: 0.842228791773772
Average Neutral Sentiment Score: 0.07630077120822636
Average Compound Sentiment Score: -0.007010636246786622
```

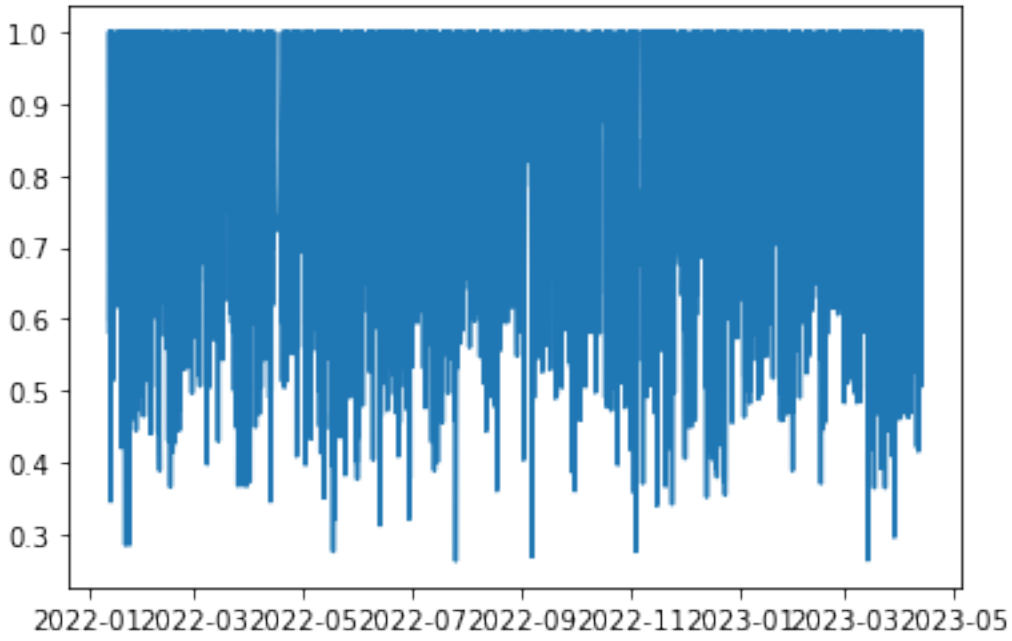
[20]:
```
plt.plot(positive_scores)
```

[20]:
```
[<matplotlib.lines.Line2D at 0x2a9deb2ffd0>]
```



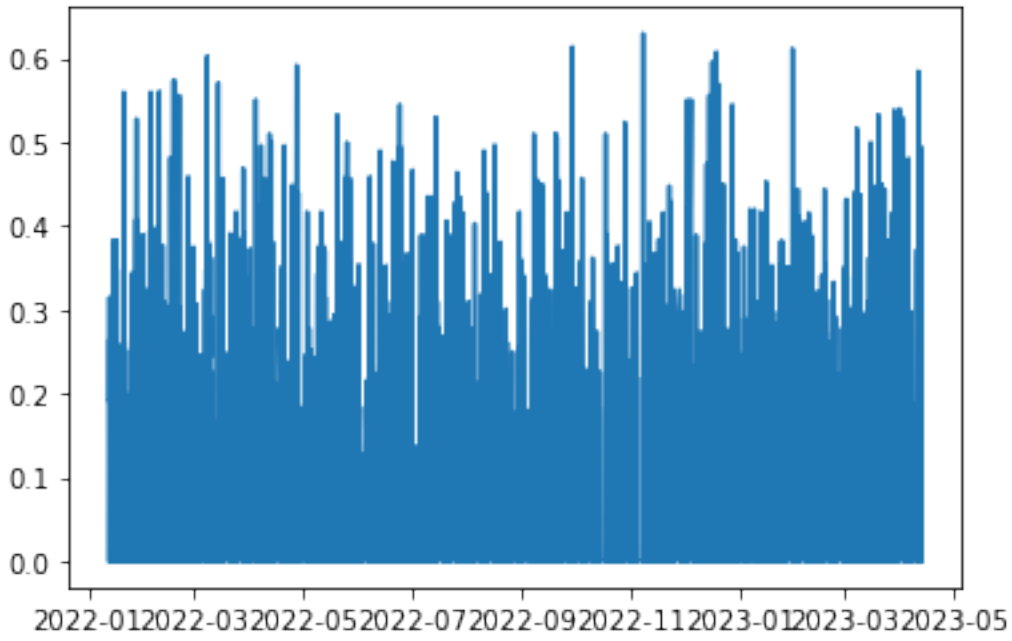
[21]:
```
plt.plot(negative_scores)
```

[21]:
```
[<matplotlib.lines.Line2D at 0x2a9e42c85e0>]
```



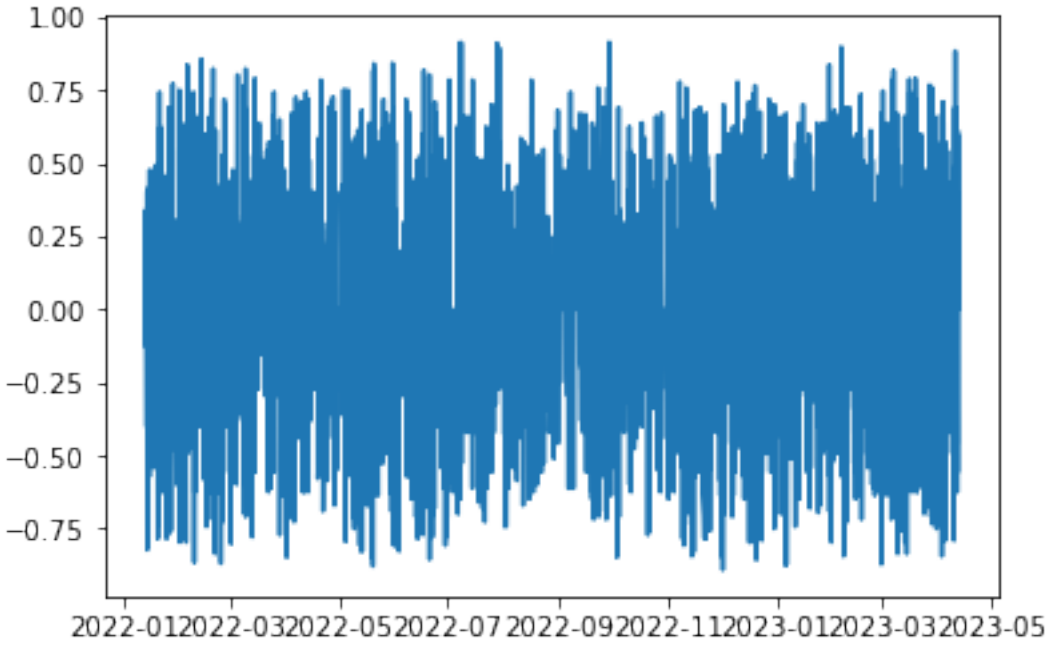
[22]:
```
plt.plot(neutral_scores)
```

[22]: [<matplotlib.lines.Line2D at 0x2a9e4776e50>]

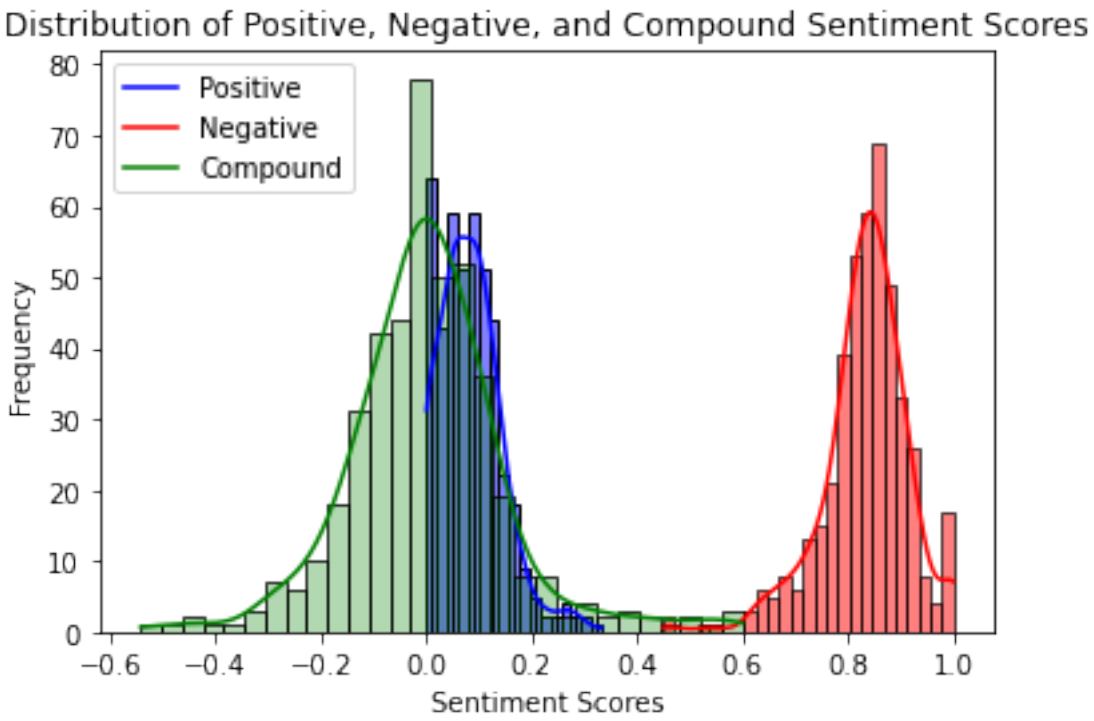


[23]:
```
plt.plot(compound_scores)
```

[23]:
```
[<matplotlib.lines.Line2D at 0x2a9e450c7c0>]
```



[24]:
```
# Create the distribution plot for the positive sentiment scores
sns.histplot(data=daily_sentiment, x='pos', kde=True, color='blue', alpha=0.5)
sns.histplot(data=daily_sentiment, x='neg', kde=True, color='red', alpha=0.5)
sns.histplot(data=daily_sentiment, x='compound', kde=True, color='green',␣
 ↪alpha=0.3)

# Set the labels and title
plt.xlabel('Sentiment Scores')
plt.ylabel('Frequency')
plt.title('Distribution of Positive, Negative, and Compound Sentiment Scores')

# Add a legend
plt.legend(labels=['Positive', 'Negative', 'Compound'])

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



[25]:
```
btc = pd.read_csv('C:/DJ Cap/Data/btc_data.csv')
```

[26]:
```
daily_sentiment
```

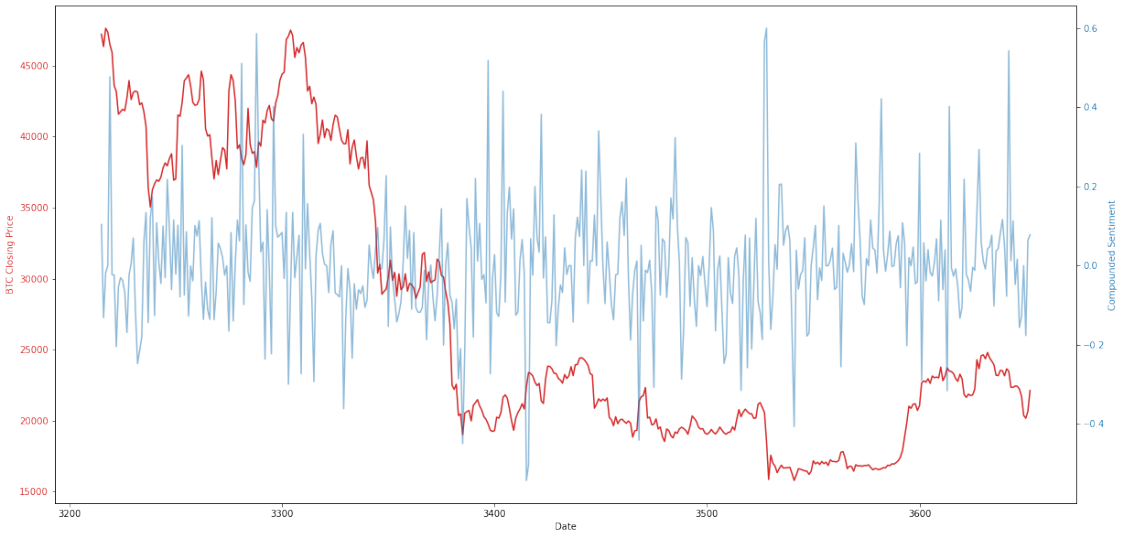
[26]:

	index	pos	neg	neu	compound
0	2022-01-12	0.025667	0.831000	0.143333	0.103867
1	2022-01-13	0.130500	0.822300	0.047200	-0.131450
2	2022-01-14	0.110400	0.775800	0.113800	-0.017550
3	2022-01-15	0.000000	1.000000	0.000000	0.000000
4	2022-01-16	0.000000	0.617000	0.383000	0.476700
..	…	…	…	…	…
451	2023-04-08	0.068667	0.931333	0.000000	-0.127267
452	2023-04-09	0.000000	1.000000	0.000000	0.000000
453	2023-04-10	0.157667	0.800333	0.042000	-0.176617
454	2023-04-11	0.034258	0.891045	0.074697	0.063267
455	2023-04-12	0.049969	0.847375	0.102656	0.077934

[438 rows x 5 columns]

[27]:
```
data = btc['o.c'][len(btc['o.c'])-len(daily_sentiment):]
index = data.index
daily_sentiment.index = index
```

[29]:
```
plt.rcParams['figure.figsize'] = (20, 10)

# Create the plot figure and axes
fig, ax1 = plt.subplots()

color = 'tab:red'
ax1.set_xlabel('Date')
ax1.set_ylabel('BTC Closing Price', color=color)
ax1.plot(data, color=color)
ax1.tick_params(axis='y', labelcolor=color)

ax2 = ax1.twinx()

color = 'tab:blue'
ax2.set_ylabel('Compounded Sentiment', color=color)
ax2.plot(daily_sentiment['compound'], color=color, alpha = 0.5)
ax2.tick_params(axis='y', labelcolor=color)
```

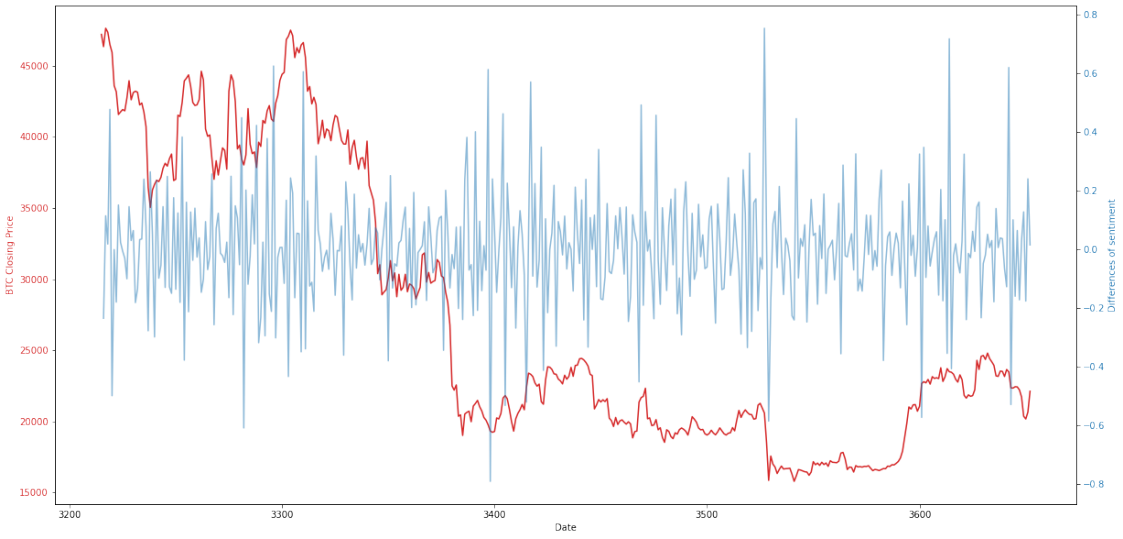


[32]:
```
#Because the sentiment has a dilay, we take the diferences to trade the dynamic␣
 ↪of the sentiment scores.
test = daily_sentiment['compound'].diff().dropna()
test
```

[32]:
```
3216   -0.235317
3217    0.113900
3218    0.017550
3219    0.476700
3220   -0.499457
          …
```

```
3648    0.028933
3649    0.127267
3650   -0.176617
3651    0.239883
3652    0.014668
Name: compound, Length: 437, dtype: float64
```

[33]:
```
plt.rcParams['figure.figsize'] = (20, 10)
# Create the plot figure and axes
fig, ax1 = plt.subplots()

color = 'tab:red'
ax1.set_xlabel('Date')
ax1.set_ylabel('BTC Closing Price', color=color)
ax1.plot(data, color=color)
ax1.tick_params(axis='y', labelcolor=color)

ax2 = ax1.twinx()  # instantiate a second axes that shares the same x-axis

color = 'tab:blue'
ax2.set_ylabel('Differences of sentiment', color=color)  # we already handled␣
 ↪the x-label with ax1
ax2.plot(test, color=color, alpha = 0.5)
ax2.tick_params(axis='y', labelcolor=color)
```



[78]:
```
#Long short
#Transform Signal in a -1,1 Signal
import numpy as np
data = btc['o.c'][len(btc['o.c'])-len(daily_sentiment['compound']):]
```

```
index = data.index
daily_sentiment.index = index

trading_signal = np.array(daily_sentiment['compound'])
y2 = []
for i in range(0,len(daily_sentiment)):
    if trading_signal[i] > 0:
        y2.append(1)
    else:
        y2.append(-1)
```

[79]:
```
#only short
trading_signal = np.array(daily_sentiment['compound'])
y1 = []
for i in range(0,len(daily_sentiment)):
    if trading_signal[i] > 0:
        y1.append(0)
    else:
        y1.append(-1)
```

[80]:
```
#only long
trading_signal = np.array(daily_sentiment['compound'])
y0 = []
for i in range(0,len(daily_sentiment)):
    if trading_signal[i] > 0:
        y0.append(1)
    else:
        y0.append(0)
```

[81]:
```
n = len(daily_sentiment['compound'])
X = btc['o.c'].pct_change().shift(-1)
X = X[len(X)-n:]
len(X)
```

[81]:
```
438
```

[82]:
```
data = btc['o.c'][len(btc['o.c'])-len(test):]
index = data.index
test.index = index
```

[83]:
```
# Mit differenzen
X1 = btc['o.c'].pct_change().shift(-1)
X1 = X1[len(X1)-len(test):]



trading_signal = np.array(test)
```

```
y_diff_sig = []
for i in range(0,len(test)):
    if trading_signal[i] > 0:
        y_diff_sig.append(-1) #Switch in dierectaion because we took␣
 ↪differences so if test > 0 -> short else long
    else:
        y_diff_sig.append(1)


#performance
perf_d_f = y_diff_sig * X1

perf_d_f = perf_d_f.dropna()

trading_days_Y = len(test)

perf_sharpe = np.sqrt(trading_days_Y) * np.mean(perf_d_f) / (np.sqrt(np.
 ↪var(perf_d_f)))
```

[84]:
```
#long Sentiment
perf0 = y0 * X

perf0 = perf0.dropna()

trading_days_Y = 365

perf_sharpe0 = np.sqrt(trading_days_Y) * np.mean(perf0) / (np.sqrt(np.
 ↪var(perf0)))
```

[85]:
```
#short Sentiment
perf1 = y1 * X

perf1 = perf1.dropna()

trading_days_Y = 365

perf_sharpe1 = np.sqrt(trading_days_Y) * np.mean(perf1) / (np.sqrt(np.
 ↪var(perf1)))
```

[86]:
```
#long short Sentiment
perf2 = y2 * X

perf2 = perf2.dropna()

trading_days_Y = 365
```

```
perf_sharpe2 = np.sqrt(trading_days_Y) * np.mean(perf2) / (np.sqrt(np.
 ↪var(perf2)))
```

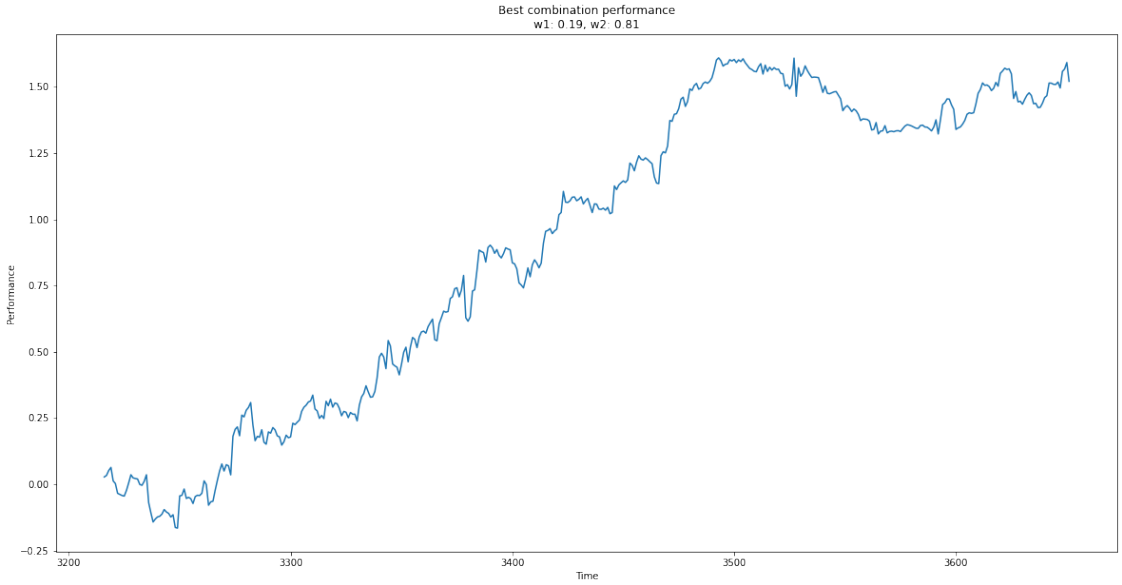
[87]:
```
#buy and hold
perf3 = X
trading_days_Y = 365

perf_sharpe3 = np.sqrt(trading_days_Y) * np.mean(perf3) / (np.sqrt(np.
 ↪var(perf3)))
```

[101]:
```
# Here we try to combine the sentiment scores withe the momentum of the score.
# S = w1 * deltaS0 + w2 * S0 -> Grid search


deltaS0 = test  #diff
S0 = daily_sentiment['compound']  #original

# Define the range and step size for w1 and w2
w1_range = np.arange(0, 1.1, 0.01)
w2_range = np.arange(0, 1.1, 0.01)

# Initialize a list to store the results
results = []

# Perform the grid search
for w1 in w1_range:
    for w2 in w2_range:
        # Ensure w1 + w2 = 1 to maintain a valid weight combination
        if w1 + w2 == 1:
            S = [w1 * dS0 + w2 * s for dS0, s in zip(deltaS0, S0)]
            results.append({'w1': w1, 'w2': w2, 'S': S})

# Create a DataFrame from the results
df = pd.DataFrame(results)

# Generate the trading signals
signals = []

for index, row in df.iterrows():
    trading_signal = np.array(row['S'])
    y_diff_and_senti = []

    # Calculate the differences
    differences = np.diff(trading_signal)

    # Generate the trading signals
    for diff in differences:
```

```
        if diff > 0:
            y_diff_and_senti.append(-1)
        else:
            y_diff_and_senti.append(1)

    signals.append(y_diff_and_senti)

# Add the trading signals to the DataFrame
df['trading_signals'] = signals

X1 = btc['o.c'].pct_change().shift(-1)
X1 = X1[len(X1)-len(test):]
X1 = X1.dropna()


# Calculate the performance
performances = []

for index, row in df.iterrows():
    perf_new = np.array(row['trading_signals']) * X1
    perf_new = perf_new[~np.isnan(perf_new)]  # Remove NaN values
    performances.append(perf_new)

df['performance'] = performances

# Calculate the Sharpe Ratio
trading_days_Y = len(deltaS0)
sharpe_ratios = []

for perf_new in df['performance']:
    sharpe_ratio = np.sqrt(trading_days_Y) * np.mean(perf_new) / np.sqrt(np.
 ↪var(perf_new))
    #sp_ann = sharpe_ratio * np.sqrt(365) #annualized (is this correct?)
    sharpe_ratios.append(sharpe_ratio)

df['sharpe_ratio'] = sharpe_ratios

# Find the best combination based on the Sharpe Ratio
best_combination = df.loc[df['sharpe_ratio'].idxmax()]

# Print the best combination
print("Best combination:\n", best_combination)

# Plot the best combination's performance
plt.plot(best_combination['performance'].cumsum())
plt.title(f"Best combination performance\nw1: {best_combination['w1']}, w2:␣
 ↪{best_combination['w2']}")
```

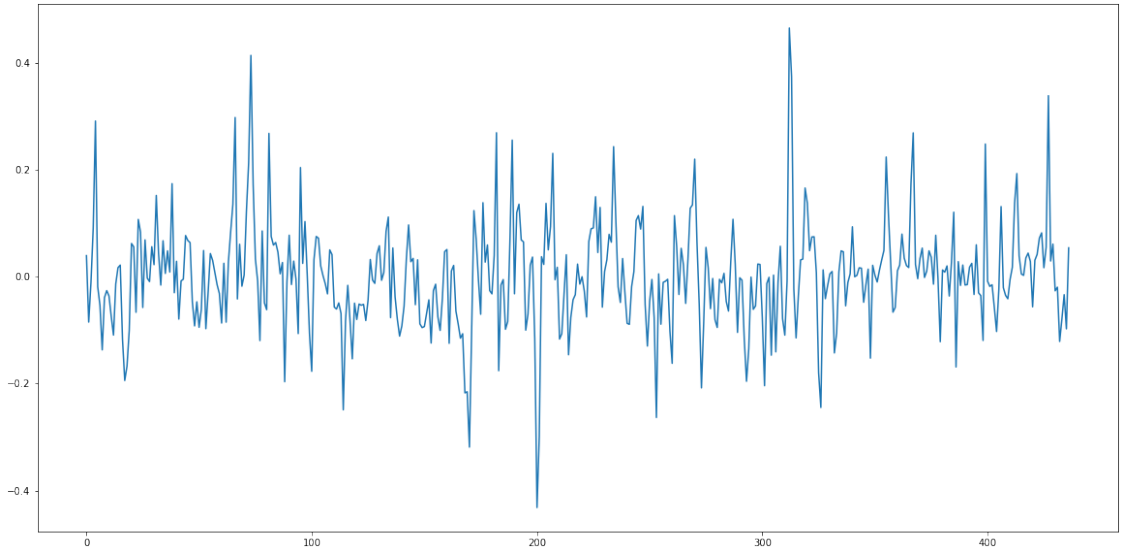
```
plt.xlabel("Time")
plt.ylabel("Performance")
plt.show()
```

```
Best combination:
 w1                                                              0.19
w2                                                              0.81
S                  [0.03942183333333334, -0.0848335, -0.010880999…
trading_signals    [1, -1, -1, -1, 1, 1, 1, -1, -1, 1, 1, 1, -1, …
performance        3216    0.027876
3217    0.005787
3218    0.01…
sharpe_ratio                                                2.265938
Name: 19, dtype: object
```



[100]:
```
#Sentiment score
plt.plot(best_combination['S'])
```

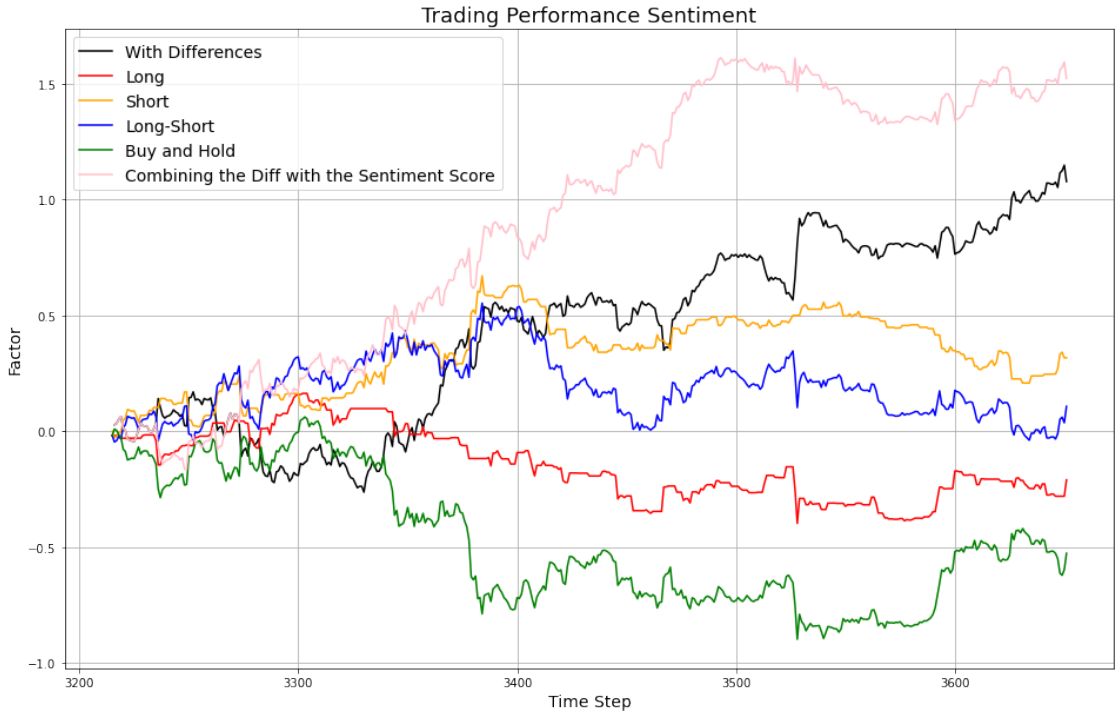
[100]: `[<matplotlib.lines.Line2D at 0x2a9f108de50>]`



[90]:
```
#Combination between the diff and Sentiment score based on best sharpe ratio
X2 = btc['o.c'].pct_change().shift(-1)
X2 = X2[len(X2)-len(test):]
X2 = X2.dropna()
y_4 = best_combination['trading_signals']
perf4 = y_4 * X2
```

[91]:
```
plt.figure(figsize=(16,10))
plt.title('Trading Performance Sentiment', fontsize = 18)
plt.ylabel('Factor', fontsize = 14)
plt.xlabel('Time Step', fontsize = 14)
plt.grid(True)
plt.plot(perf_d_f.cumsum() , label='With Differences', color = 'black')
plt.plot(perf0.cumsum() , label='Long', color = 'red')
plt.plot(perf1.cumsum() , label='Short', color = 'orange')
plt.plot(perf2.cumsum() , label='Long-Short', color = 'blue')
plt.plot(perf3.cumsum() , label='Buy and Hold', color = 'green')
plt.plot(perf4.cumsum() , label='Combining the Diff with the Sentiment Score',␣
 ↪color = 'pink')
plt.legend(loc='best', fontsize = 14)
```

[91]:
```
<matplotlib.legend.Legend at 0x2a9eff89520>
```



In conclusion, we utilized the sentiment score as a trading signal. We included the generated score's momentum by combining the score's difference with the original score value. This can be observed in the Pink Curve on the Performance plot. Due to Refinitive's limited 15 Month past News data, we chose not to include the sentiment score in our ML Model (Random Forest and XGBoost), as we need more data to train the models. However, it would be interesting to investigate whether this sentiment score could enhance Bubble prediction, as the indicator's performance appears highly encouraging.