```
import pandas as pd
price = pd.read_csv('/content/Bitcoin Historical Data (2).csv')
sentiment=pd.read_csv('/content/bitcoin_sentiments_21_24.csv')
```

```
price
```

| | Date | Price | Open | High | Low | Vol. | Change % |
|---|---|---|---|---|---|---|---|
| **0** | 31-12-2023 | 42,272.5 | 42,141.6 | 42,878.8 | 41,971.4 | 35.58K | 0.32% |
| **1** | 30-12-2023 | 42,136.7 | 42,074.7 | 42,592.2 | 41,527.3 | 35.18K | 0.15% |
| **2** | 29-12-2023 | 42,072.4 | 42,581.1 | 43,108.0 | 41,459.0 | 60.98K | -1.19% |
| **3** | 28-12-2023 | 42,581.1 | 43,446.5 | 43,782.6 | 42,309.3 | 49.84K | -1.99% |
| **4** | 27-12-2023 | 43,446.5 | 42,514.3 | 43,676.7 | 42,115.3 | 50.10K | 2.20% |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **1090** | 05-01-2021 | 33,991.5 | 32,015.4 | 34,414.7 | 30,010.5 | 202.13K | 6.15% |
| **1091** | 04-01-2021 | 32,022.6 | 33,016.6 | 33,587.5 | 28,204.5 | 255.27K | -2.84% |
| **1092** | 03-01-2021 | 32,958.9 | 32,192.9 | 34,755.9 | 32,029.6 | 155.21K | 2.38% |
| **1093** | 02-01-2021 | 32,193.3 | 29,359.7 | 33,233.5 | 29,008.0 | 240.87K | 9.65% |
| **1094** | 01-01-2021 | 29,359.9 | 28,951.7 | 29,627.1 | 28,712.4 | 100.90K | 1.42% |

1095 rows × 7 columns

```
price = price.iloc[::-1].reset_index(drop=True)
price
```

| | Date | Price | Open | High | Low | Vol. | Change % |
|---|---|---|---|---|---|---|---|
| **0** | 01-01-2021 | 29,359.9 | 28,951.7 | 29,627.1 | 28,712.4 | 100.90K | 1.42% |
| **1** | 02-01-2021 | 32,193.3 | 29,359.7 | 33,233.5 | 29,008.0 | 240.87K | 9.65% |
| **2** | 03-01-2021 | 32,958.9 | 32,192.9 | 34,755.9 | 32,029.6 | 155.21K | 2.38% |
| **3** | 04-01-2021 | 32,022.6 | 33,016.6 | 33,587.5 | 28,204.5 | 255.27K | -2.84% |
| **4** | 05-01-2021 | 33,991.5 | 32,015.4 | 34,414.7 | 30,010.5 | 202.13K | 6.15% |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **1090** | 27-12-2023 | 43,446.5 | 42,514.3 | 43,676.7 | 42,115.3 | 50.10K | 2.20% |
| **1091** | 28-12-2023 | 42,581.1 | 43,446.5 | 43,782.6 | 42,309.3 | 49.84K | -1.99% |
| **1092** | 29-12-2023 | 42,072.4 | 42,581.1 | 43,108.0 | 41,459.0 | 60.98K | -1.19% |
| **1093** | 30-12-2023 | 42,136.7 | 42,074.7 | 42,592.2 | 41,527.3 | 35.18K | 0.15% |
| **1094** | 31-12-2023 | 42,272.5 | 42,141.6 | 42,878.8 | 41,971.4 | 35.58K | 0.32% |

1095 rows × 7 columns

```
price.dtypes
```

| | 0 |
|---|---|
| **Date** | object |
| **Price** | object |
| **Open** | object |
| **High** | object |
| **Low** | object |
| **Vol.** | object |
| **Change %** | object |

**dtype:** object

```
price['Date'] = pd.to_datetime(price['Date'], format='%d-%m-%Y', errors='coerce')
price['Date'] = price['Date'].dt.date
price
```

| | Date | Price | Open | High | Low | Vol. | Change % |
|---|---|---|---|---|---|---|---|
| **0** | 2021-01-01 | 29,359.9 | 28,951.7 | 29,627.1 | 28,712.4 | 100.90K | 1.42% |
| **1** | 2021-01-02 | 32,193.3 | 29,359.7 | 33,233.5 | 29,008.0 | 240.87K | 9.65% |
| **2** | 2021-01-03 | 32,958.9 | 32,192.9 | 34,755.9 | 32,029.6 | 155.21K | 2.38% |
| **3** | 2021-01-04 | 32,022.6 | 33,016.6 | 33,587.5 | 28,204.5 | 255.27K | -2.84% |
| **4** | 2021-01-05 | 33,991.5 | 32,015.4 | 34,414.7 | 30,010.5 | 202.13K | 6.15% |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **1090** | 2023-12-27 | 43,446.5 | 42,514.3 | 43,676.7 | 42,115.3 | 50.10K | 2.20% |
| **1091** | 2023-12-28 | 42,581.1 | 43,446.5 | 43,782.6 | 42,309.3 | 49.84K | -1.99% |
| **1092** | 2023-12-29 | 42,072.4 | 42,581.1 | 43,108.0 | 41,459.0 | 60.98K | -1.19% |
| **1093** | 2023-12-30 | 42,136.7 | 42,074.7 | 42,592.2 | 41,527.3 | 35.18K | 0.15% |
| **1094** | 2023-12-31 | 42,272.5 | 42,141.6 | 42,878.8 | 41,971.4 | 35.58K | 0.32% |

1095 rows × 7 columns

```
def convert_volume(vol_str):
    if isinstance(vol_str, str):
        if vol_str.endswith('K'):
            return float(vol_str[:-1]) * 1000
        elif vol_str.endswith('M'):
            return float(vol_str[:-1]) * 1000000
        elif vol_str.endswith('B'):  # Handle billions
            return float(vol_str[:-1]) * 1000000000
        else:
```

```
            try:
                print(vol_str)
                return float(vol_str)
            except ValueError:
                print(vol_str)
                return None  # Use None instead of empty return for better clarity
    else:
        return vol_str  # Return the value unchanged if it's not a string

# Applying the function to the DataFrame
price['Vol.'] = price['Vol.'].apply(convert_volume)

# Convert other columns as before
price['Price'] = price['Price'].astype(str).str.replace(',', '').astype(float)
price['Open'] = price['Open'].astype(str).str.replace(',', '').astype(float)
price['High'] = price['High'].astype(str).str.replace(',', '').astype(float)
price['Low'] = price['Low'].astype(str).str.replace(',', '').astype(float)
price['Change %'] = price['Change %'].astype(str).str.replace('%', '').str.replace(',', '')

# Final type casting to ensure all columns are of the correct type
price['Price'] = price['Price'].astype(float)
price['Open'] = price['Open'].astype(float)
price['High'] = price['High'].astype(float)
price['Low'] = price['Low'].astype(float)
price['Vol.'] = price['Vol.'].astype(float)
price['Change %'] = price['Change %'].astype(float)



price.isnull().sum()
```

| | 0 |
|---|---|
| **Date** | 0 |
| **Price** | 0 |
| **Open** | 0 |
| **High** | 0 |
| **Low** | 0 |
| **Vol.** | 0 |
| **Change %** | 0 |

**dtype:** int64

```
price.describe()
```

| | Price | Open | High | Low | Vol. | Change % |
|---|---|---|---|---|---|---|
| **count** | 1095.000000 | 1095.000000 | 1095.000000 | 1095.000000 | 1.095000e+03 | 1095.000000 |
| **mean** | 34816.069863 | 34804.290776 | 35636.033333 | 33895.309589 | 5.537300e+07 | 0.092219 |
| **std** | 12546.311251 | 12545.323573 | 12915.894346 | 12105.296359 | 3.274580e+08 | 3.396028 |
| **min** | 15776.200000 | 15776.600000 | 16274.600000 | 15504.200000 | 2.600000e+02 | -15.630000 |
| **25%** | 24665.550000 | 24665.450000 | 25235.300000 | 24222.950000 | 5.592500e+04 | -1.460000 |
| **50%** | 32241.300000 | 32192.900000 | 33307.700000 | 30850.000000 | 9.727000e+04 | -0.040000 |
| **75%** | 43484.500000 | 43484.650000 | 44247.300000 | 42478.900000 | 2.097650e+05 | 1.600000 |
| **max** | 67527.900000 | 67528.700000 | 68990.600000 | 66334.900000 | 4.470000e+09 | 19.410000 |

```
sentiment
```

| | Date | Short Description | Accurate Sentiments |
|---|---|---|---|
| **0** | 2021-11-05 04:42:00 | Bitcoin price is consolidating near the USD 62... | 0.998558 |
| **1** | 2021-11-05 08:15:00 | Congress could finally approve or reject the m... | 0.000000 |
| **2** | 2021-11-05 10:24:00 | Bitcoin increasingly becoming a political inst... | 0.000000 |
| **3** | 2021-11-05 16:58:00 | There is still potential for the price of bitc... | 0.999458 |
| **4** | 2021-11-05 21:00:00 | 'Several companies' are looking to Latin Ameri... | 0.000000 |
| **...** | ... | ... | ... |
| **11290** | 2024-09-12 00:00:00 | The government of El Salvador has been buying ... | 0.000000 |
| **11291** | 2024-09-12 00:00:00 | According to data from mempool.space, transact... | 0.997017 |

```
sentiment = sentiment.drop('Short Description', axis=1)
sentiment
```

| | Date | Accurate Sentiments |
|---|---|---|
| **0** | 2021-11-05 04:42:00 | 0.998558 |
| **1** | 2021-11-05 08:15:00 | 0.000000 |
| **2** | 2021-11-05 10:24:00 | 0.000000 |
| **3** | 2021-11-05 16:58:00 | 0.999458 |
| **4** | 2021-11-05 21:00:00 | 0.000000 |
| **...** | ... | ... |
| **11290** | 2024-09-12 00:00:00 | 0.000000 |
| **11291** | 2024-09-12 00:00:00 | 0.997017 |
| **11292** | 2024-09-12 00:00:00 | 0.000000 |
| **11293** | 2024-09-12 00:00:00 | 0.000000 |
| **11294** | 2024-09-12 00:00:00 | 0.000000 |

11295 rows × 2 columns

```
sentiment.dtypes
```

| | 0 |
|---|---|
| **Date** | object |
| **Accurate Sentiments** | float64 |

**dtype:** object

```
sentiment['Date'] = pd.to_datetime(sentiment['Date'], errors='coerce')
sentiment['Date'] = sentiment['Date'].dt.date
sentiment
```

| | Date | Accurate Sentiments |
|---|---|---|
| **0** | 2021-11-05 | 0.998558 |
| **1** | 2021-11-05 | 0.000000 |
| **2** | 2021-11-05 | 0.000000 |
| **3** | 2021-11-05 | 0.999458 |
| **4** | 2021-11-05 | 0.000000 |
| **...** | ... | ... |
| **11290** | 2024-09-12 | 0.000000 |
| **11291** | 2024-09-12 | 0.997017 |
| **11292** | 2024-09-12 | 0.000000 |
| **11293** | 2024-09-12 | 0.000000 |
| **11294** | 2024-09-12 | 0.000000 |

11295 rows × 2 columns

```
sentiment.isnull().sum()
```

| | 0 |
|---|---|
| **Date** | 0 |
| **Accurate Sentiments** | 0 |

**dtype:** int64

```
# Sort the sentiment dataset by date
sentiment = sentiment.sort_values(by='Date')
price = price.sort_values(by='Date')


cumulative_sentiment_data = []

current_date = None
cumulative_sentiment = 0

for index, row in sentiment.iterrows():
    if current_date is None:
        current_date = row['Date']
        cumulative_sentiment = row['Accurate Sentiments']
    elif row['Date'] == current_date:
        cumulative_sentiment += row['Accurate Sentiments']
    else:
        cumulative_sentiment_data.append({'Date': current_date, 'Cumulative Sentiment': cum

        current_date = row['Date']
        cumulative_sentiment = row['Accurate Sentiments']
```

```
cumulative_sentiment_data.append({'Date': current_date, 'Cumulative Sentiment': cumulative_
sentiment = pd.DataFrame(cumulative_sentiment_data)
sentiment
```

| | Date | Cumulative Sentiment |
|---|---|---|
| **0** | 2021-11-05 | 1.998016 |
| **1** | 2021-11-06 | 0.000000 |
| **2** | 2021-11-08 | -0.839764 |
| **3** | 2021-11-09 | 0.999633 |
| **4** | 2021-11-10 | -0.996722 |
| **...** | ... | ... |
| **882** | 2024-09-08 | -1.301715 |
| **883** | 2024-09-09 | 7.035380 |
| **884** | 2024-09-10 | 13.908900 |
| **885** | 2024-09-11 | -10.541270 |
| **886** | 2024-09-12 | 3.877340 |

887 rows × 2 columns

```
print((sentiment['Cumulative Sentiment'] == 0.000).sum())
```

```
19
```

```
print("Minimum Date in price database:", price['Date'].min())
print("Maximum Date in price database:", price['Date'].max())
print("Minimum Date in sentiment database:", sentiment['Date'].min())
print("Maximum Date in sentiment database:", sentiment['Date'].max())
```

```
Minimum Date in price database: 2021-01-01
Maximum Date in price database: 2023-12-31
Minimum Date in sentiment database: 2021-11-05
Maximum Date in sentiment database: 2024-09-12
```

```
start_date = pd.to_datetime('2021-11-05').date()
end_date = pd.to_datetime('2023-12-31').date()
price = price[(price['Date'] >= start_date) & (price['Date'] <= end_date)]
sentiment = sentiment[(sentiment['Date'] >= start_date) & (sentiment['Date'] <= end_date)]


final_df = pd.merge(price, sentiment, on='Date', how='left')
final_df
```

| | Date | Price | Open | High | Low | Vol. | Change % | Cumulative Sentiment |
|---|---|---|---|---|---|---|---|---|
| **0** | 2021-11-05 | 60974.3 | 61411.5 | 62560.3 | 60742.4 | 44460.0 | -0.71 | 1.998016 |
| **1** | 2021-11-06 | 61483.9 | 60973.2 | 61543.2 | 60093.6 | 34890.0 | 0.84 | 0.000000 |
| **2** | 2021-11-07 | 63273.2 | 61483.8 | 63273.2 | 61347.2 | 34340.0 | 2.91 | NaN |
| **3** | 2021-11-08 | 67527.9 | 63276.4 | 67763.3 | 63276.4 | 81080.0 | 6.72 | -0.839764 |
| **4** | 2021-11-09 | 66904.4 | 67528.7 | 68493.3 | 66334.9 | 66130.0 | -0.92 | 0.999633 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... |
| **782** | 2023-12-27 | 43446.5 | 42514.3 | 43676.7 | 42115.3 | 50100.0 | 2.20 | NaN |
| **783** | 2023-12-28 | 42581.1 | 43446.5 | 43782.6 | 42309.3 | 49840.0 | -1.99 | NaN |

```
final_df.isnull().sum()
```

| | 0 |
|---|---|
| **Date** | 0 |
| **Price** | 0 |
| **Open** | 0 |
| **High** | 0 |
| **Low** | 0 |
| **Vol.** | 0 |
| **Change %** | 0 |
| **Cumulative Sentiment** | 30 |

**dtype:** int64

```
final_df['sentiment_null'] = 0
final_df.loc[final_df['Cumulative Sentiment'].isnull(), 'sentiment_null'] = 1
final_df
```

| | Date | Price | Open | High | Low | Vol. | Change % | Cumulative Sentiment | sentiment_n |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 2021-11-05 | 60974.3 | 61411.5 | 62560.3 | 60742.4 | 44460.0 | -0.71 | 1.998016 | |
| **1** | 2021-11-06 | 61483.9 | 60973.2 | 61543.2 | 60093.6 | 34890.0 | 0.84 | 0.000000 | |
| **2** | 2021-11-07 | 63273.2 | 61483.8 | 63273.2 | 61347.2 | 34340.0 | 2.91 | NaN | |
| **3** | 2021-11-08 | 67527.9 | 63276.4 | 67763.3 | 63276.4 | 81080.0 | 6.72 | -0.839764 | |
| **4** | 2021-11-09 | 66904.4 | 67528.7 | 68493.3 | 66334.9 | 66130.0 | -0.92 | 0.999633 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | |
| **782** | 2023-12-27 | 43446.5 | 42514.3 | 43676.7 | 42115.3 | 50100.0 | 2.20 | NaN | |
| **783** | 2023-12-28 | 42581.1 | 43446.5 | 43782.6 | 42309.3 | 49840.0 | -1.99 | NaN | |

```
if pd.isnull(final_df['Cumulative Sentiment'].iloc[0]):
    for i in range(1, len(final_df)):
        if pd.notnull(final_df['Cumulative Sentiment'].iloc[i]):
            final_df.loc[0, 'Cumulative Sentiment'] = final_df['Cumulative Sentiment'].iloc
            break

for i in range(1, len(final_df) - 1):
    if pd.isnull(final_df['Cumulative Sentiment'].iloc[i]):
        c1 = 1
        while pd.isnull(final_df['Cumulative Sentiment'].iloc[i - c1]):
            c1 += 1
        pred_val = final_df['Cumulative Sentiment'].iloc[i - c1]

        c2 = 1
        while pd.isnull(final_df['Cumulative Sentiment'].iloc[i + c2]):
            c2 += 1
        succ_val = final_df['Cumulative Sentiment'].iloc[i + c2]

        if pd.notnull(pred_val) and pd.notnull(succ_val):
            final_df.loc[i, 'Cumulative Sentiment'] = (pred_val + succ_val) / 2

if pd.isnull(final_df['Cumulative Sentiment'].iloc[-1]):
    for i in range(len(final_df) - 2, -1, -1):
        if pd.notnull(final_df['Cumulative Sentiment'].iloc[i]):
            final_df.loc[len(final_df) - 1, 'Cumulative Sentiment'] = final_df['Cumulative
            break

print(final_df.isnull().sum())
```

```
Date                    0
Price                   0
Open                    0
```

```
High                    0
Low                     0
Vol.                    0
Change %                0
Cumulative Sentiment    0
sentiment_null          0
dtype: int64
```

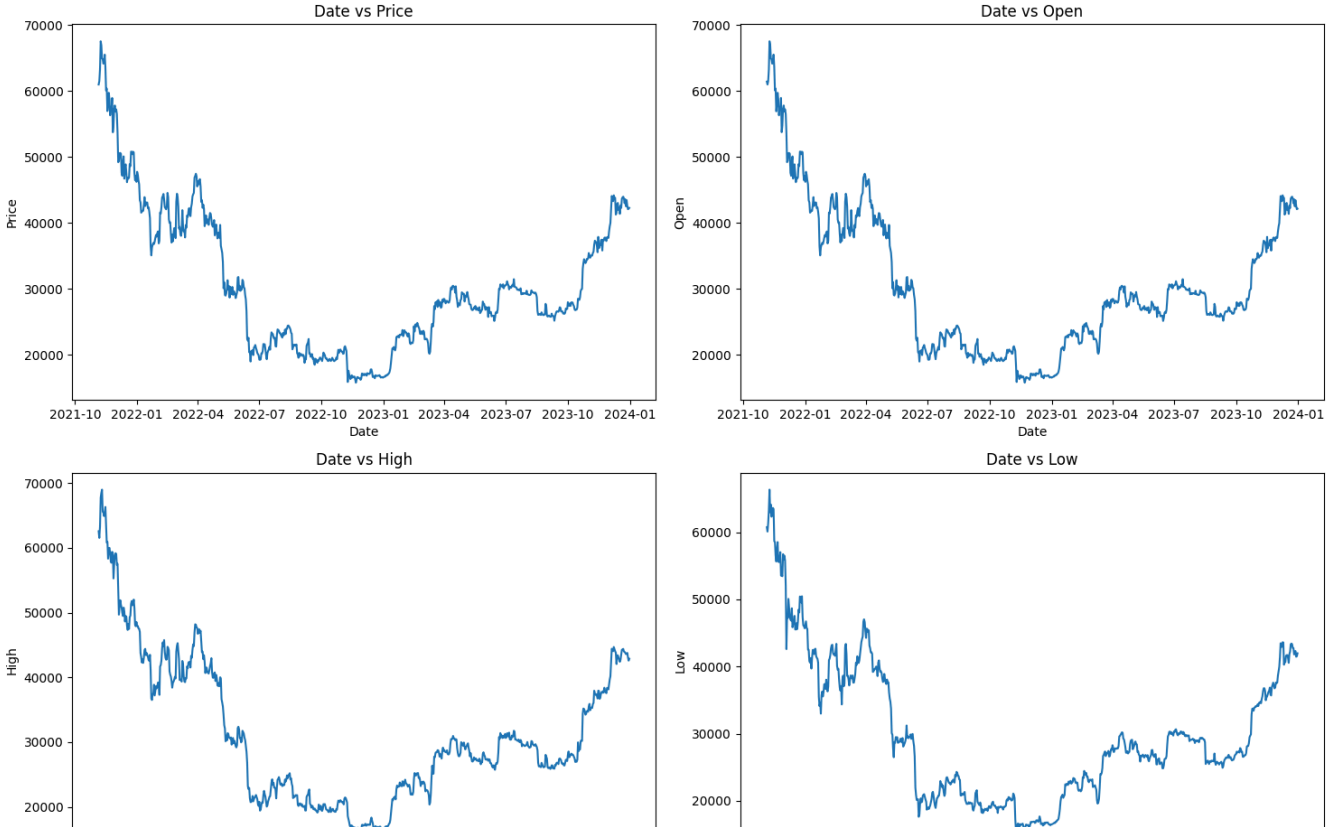
```
final_df
```

| | Date | Price | Open | High | Low | Vol. | Change % | Cumulative Sentiment | sentiment_n |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 2021-11-05 | 60974.3 | 61411.5 | 62560.3 | 60742.4 | 44460.0 | -0.71 | 1.998016 | |
| **1** | 2021-11-06 | 61483.9 | 60973.2 | 61543.2 | 60093.6 | 34890.0 | 0.84 | 0.000000 | |
| **2** | 2021-11-07 | 63273.2 | 61483.8 | 63273.2 | 61347.2 | 34340.0 | 2.91 | -0.419882 | |
| **3** | 2021-11-08 | 67527.9 | 63276.4 | 67763.3 | 63276.4 | 81080.0 | 6.72 | -0.839764 | |
| **4** | 2021-11-09 | 66904.4 | 67528.7 | 68493.3 | 66334.9 | 66130.0 | -0.92 | 0.999633 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | |
| **782** | 2023-12-27 | 43446.5 | 42514.3 | 43676.7 | 42115.3 | 50100.0 | 2.20 | 0.999580 | |
| **783** | 2023-12-28 | 42581.1 | 43446.5 | 43782.6 | 42309.3 | 49840.0 | -1.99 | 0.999580 | |

```
final_df.to_csv('data_collection.csv', index=False)
```

```
import matplotlib.pyplot as plt

fig, axes = plt.subplots(nrows=4, ncols=2, figsize=(15, 20))

axes = axes.flatten()


# Plot 1: Date vs Price
axes[0].plot(final_df['Date'], final_df['Price'])
axes[0].set_xlabel('Date')
axes[0].set_ylabel('Price')
axes[0].set_title('Date vs Price')


# Plot 2: Date vs Open
axes[1].plot(final_df['Date'], final_df['Open'])
axes[1].set_xlabel('Date')
axes[1].set_ylabel('Open')
axes[1].set_title('Date vs Open')
```

```
# Plot 3: Date vs High
axes[2].plot(final_df['Date'], final_df['High'])
axes[2].set_xlabel('Date')
axes[2].set_ylabel('High')
axes[2].set_title('Date vs High')

# Plot 4: Date vs Low
axes[3].plot(final_df['Date'], final_df['Low'])
axes[3].set_xlabel('Date')
axes[3].set_ylabel('Low')
axes[3].set_title('Date vs Low')

# Plot 5: Date vs Volume
axes[4].plot(final_df['Date'], final_df['Vol.'])
axes[4].set_xlabel('Date')
axes[4].set_ylabel('Volume')
axes[4].set_title('Date vs Volume')

# Plot 6: Date vs Change %
axes[5].plot(final_df['Date'], final_df['Change %'])
axes[5].set_xlabel('Date')
axes[5].set_ylabel('Change %')
axes[5].set_title('Date vs Change %')

# Plot 7: Date vs Cumulative Sentiment
axes[6].plot(final_df['Date'], final_df['Cumulative Sentiment'])
axes[6].set_xlabel('Date')
axes[6].set_ylabel('Cumulative Sentiment')
axes[6].set_title('Date vs Cumulative Sentiment')



# Adjust layout to prevent overlapping
plt.tight_layout()

plt.show()
```

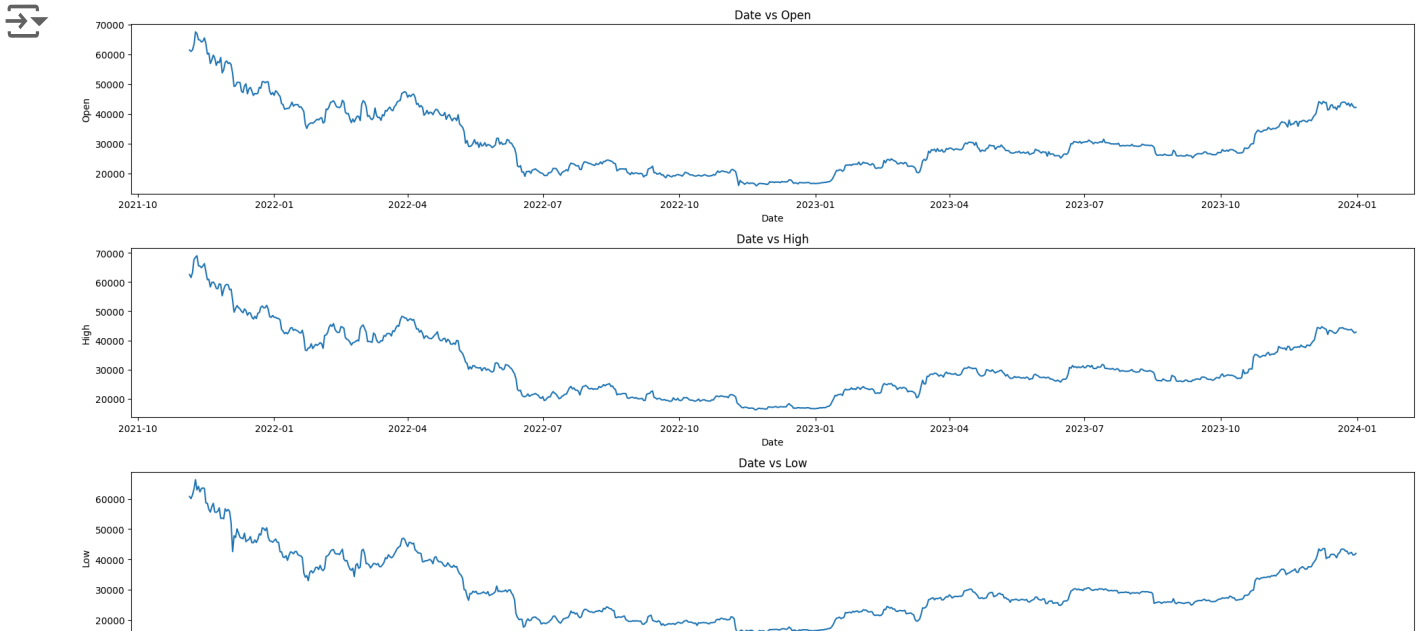

Date vs Price
Price
Date
70000
60000
50000
40000
30000
20000
2021-10
2022-01
2022-04
2022-07
2022-10
2023-01
2023-04
2023-07
2023-10
2024-01


Date vs Open
Open
Date
70000
60000
50000
40000
30000
20000
2021-10
2022-01
2022-04
2022-07
2022-10
2023-01
2023-04
2023-07
2023-10
2024-01

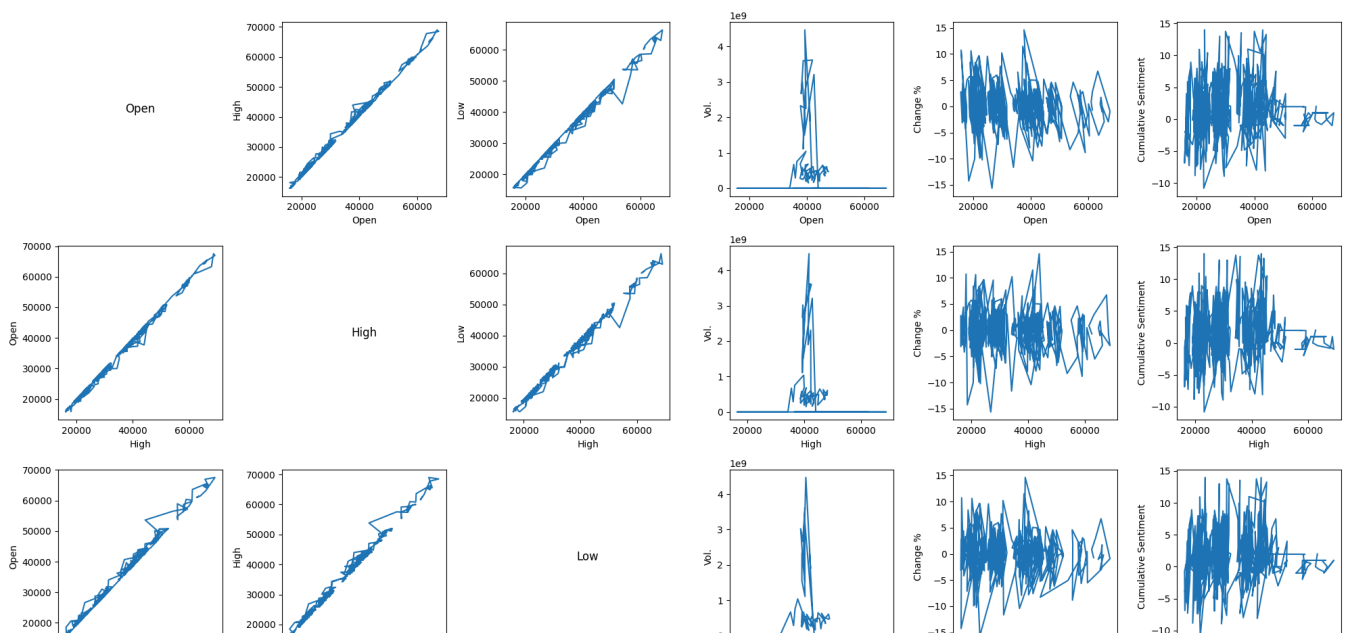

Date vs High
High
70000
60000
50000
40000
30000
20000


Date vs Low
Low
60000
50000
40000
30000
20000

```
import matplotlib.pyplot as plt

features = ['Open', 'High', 'Low', 'Vol.', 'Change %', 'Cumulative Sentiment']

fig, axes = plt.subplots(len(features), 1, figsize=(20, 20)) # Changed to 1 column

for i, feature1 in enumerate(features):
  axes[i].plot(final_df['Date'], final_df[feature1]) # Now axes[i] refers to a single Axes
  axes[i].set_xlabel('Date')
  axes[i].set_ylabel(feature1)
  axes[i].set_title('Date vs '+ feature1) # Corrected title formatting


plt.tight_layout()
plt.show()
```

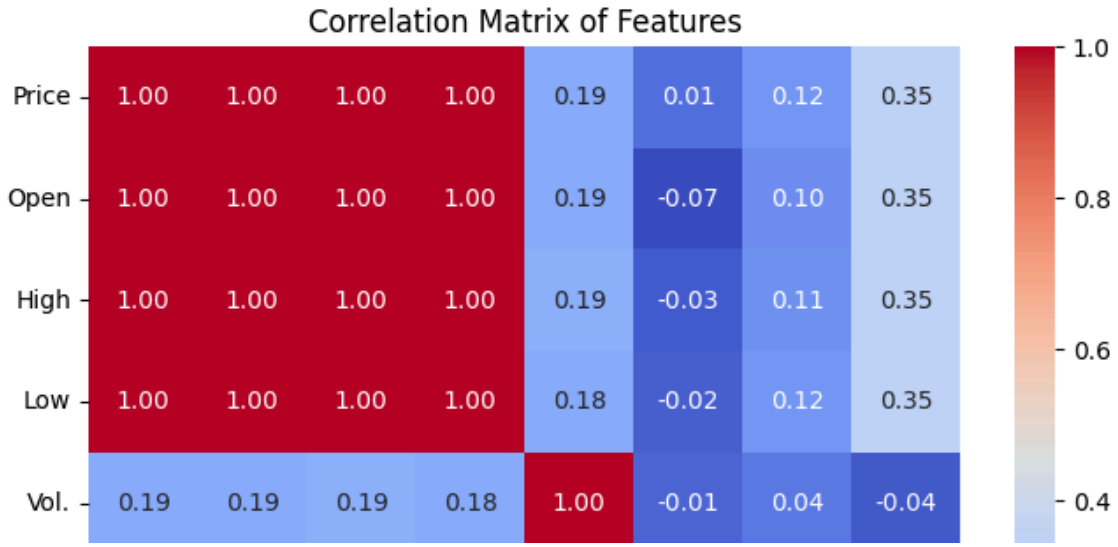


```
features = ['Open', 'High', 'Low', 'Vol.', 'Change %', 'Cumulative Sentiment']

fig, axes = plt.subplots(len(features), len(features), figsize=(20, 20))

for i, feature1 in enumerate(features):
    for j, feature2 in enumerate(features):
        if i == j:
          axes[i, j].text(0.5, 0.5, f"{feature1}", ha='center', va='center', fontsize=12)
          axes[i, j].axis('off')

        else:
          axes[i, j].plot(final_df[feature1], final_df[feature2])
          axes[i, j].set_xlabel(feature1)
          axes[i, j].set_ylabel(feature2)


plt.tight_layout()
plt.show()
```

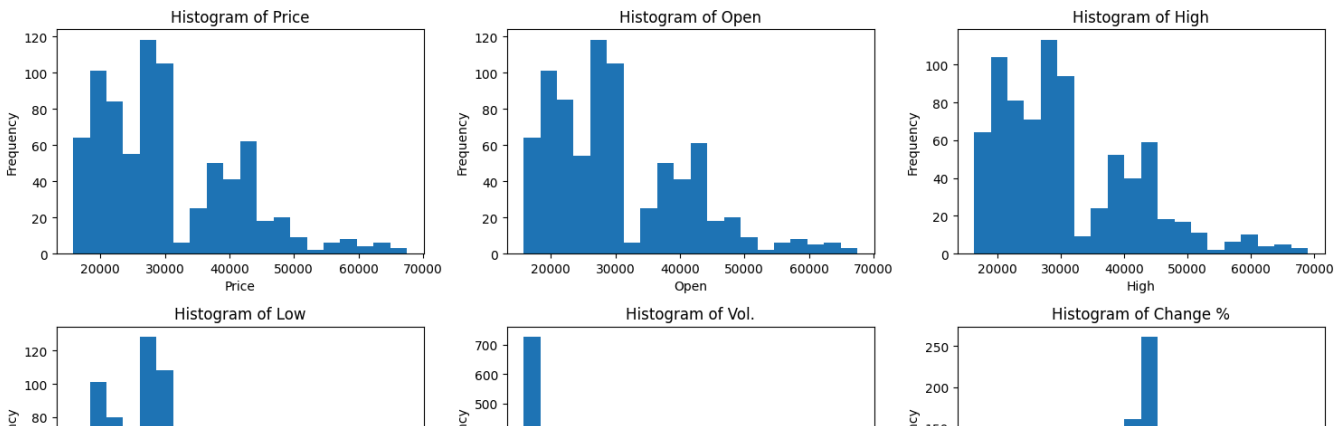


intersting observation: change and cumulative sentiment have high corerelation which is not expected as they are form differnt datasets, hence this proves that twiter sentiment analysis has high weight to predict price of bitcoin.

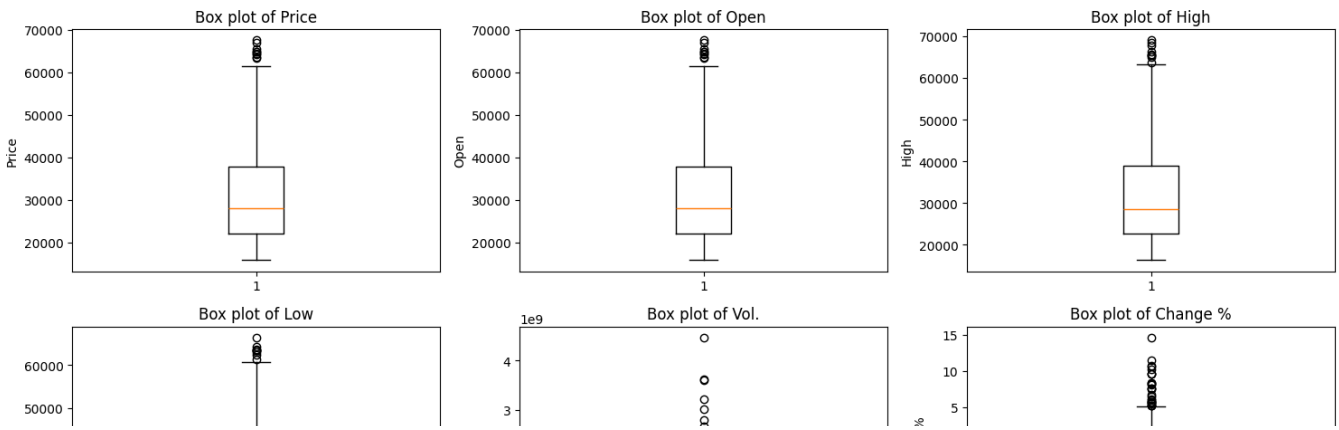
```
import seaborn as sns
features= ['Price','Open', 'High', 'Low', 'Vol.', 'Change %', 'Cumulative Sentiment','senti
correlation_matrix = final_df[features].corr()
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix of Features')
plt.show()
```




```
plt.figure(figsize=(15, 10))
for i, col in enumerate(features):
    plt.subplot(3, 3, i + 1)
    plt.hist(final_df[col], bins=20)
    plt.title(f'Histogram of {col}')
    plt.xlabel(col)
    plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```




```
plt.figure(figsize=(15, 10))
for i, col in enumerate(features):
    plt.subplot(3, 3, i + 1)
    plt.boxplot(final_df[col])
    plt.title(f'Box plot of {col}')
    plt.ylabel(col)
plt.tight_layout()
plt.show()
```


Box plot of Price
Price
70000
60000
50000
40000
30000
20000
1
Box plot of Open
Open
70000
60000
50000
40000
30000
20000
1
Box plot of High
High
70000
60000
50000
40000
30000
20000
1
Box plot of Low
60000
50000
Box plot of Vol.
1e9
4
3
Box plot of Change %
%
15
10
5

final_df

| | Date | Price | Open | High | Low | Vol. | Change % | Cumulative Sentiment | sentiment_n |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 2021-11-05 | 60974.3 | 61411.5 | 62560.3 | 60742.4 | 44460.0 | -0.71 | 1.998016 | |
| **1** | 2021-11-06 | 61483.9 | 60973.2 | 61543.2 | 60093.6 | 34890.0 | 0.84 | 0.000000 | |
| **2** | 2021-11-07 | 63273.2 | 61483.8 | 63273.2 | 61347.2 | 34340.0 | 2.91 | -0.419882 | |
| **3** | 2021-11-08 | 67527.9 | 63276.4 | 67763.3 | 63276.4 | 81080.0 | 6.72 | -0.839764 | |
| **4** | 2021-11-09 | 66904.4 | 67528.7 | 68493.3 | 66334.9 | 66130.0 | -0.92 | 0.999633 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | |
| **782** | 2023-12-27 | 43446.5 | 42514.3 | 43676.7 | 42115.3 | 50100.0 | 2.20 | 0.999580 | |
| **783** | 2023-12-28 | 42581.1 | 43446.5 | 43782.6 | 42309.3 | 49840.0 | -1.99 | 0.999580 | |

```
final_df['difference'] = final_df['High'] - final_df['Low']
final_df = final_df.drop(['Open'], axis=1)
final_df
```

| | Date | Price | High | Low | Vol. | Change % | Cumulative Sentiment | sentiment_null | dif |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 2021-11-05 | 60974.3 | 62560.3 | 60742.4 | 44460.0 | -0.71 | 1.998016 | 0 | |
| **1** | 2021-11-06 | 61483.9 | 61543.2 | 60093.6 | 34890.0 | 0.84 | 0.000000 | 0 | |
| **2** | 2021-11-07 | 63273.2 | 63273.2 | 61347.2 | 34340.0 | 2.91 | -0.419882 | 1 | |
| **3** | 2021-11-08 | 67527.9 | 67763.3 | 63276.4 | 81080.0 | 6.72 | -0.839764 | 0 | |
| **4** | 2021-11-09 | 66904.4 | 68493.3 | 66334.9 | 66130.0 | -0.92 | 0.999633 | 0 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | |
| **782** | 2023-12-27 | 43446.5 | 43676.7 | 42115.3 | 50100.0 | 2.20 | 0.999580 | 1 | |
| **783** | 2023-12-28 | 42581.1 | 43782.6 | 42309.3 | 49840.0 | -1.99 | 0.999580 | 1 | |

```
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsRegressor
```

```
from sklearn.metrics import mean_squared_error


X = final_df.drop('Price', axis=1)
y = final_df['Price']

X['Date'] = pd.to_datetime(X['Date']).apply(lambda date: date.toordinal())

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

knn_model = KNeighborsRegressor(n_neighbors=5)
knn_model.fit(X_train, y_train)

y_pred = knn_model.predict(X_test)



from sklearn.metrics import r2_score, mean_absolute_error

mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse}")

r2 = r2_score(y_test, y_pred)
print(f"R-squared: {r2}")

mae = mean_absolute_error(y_test, y_pred)
print(f"Mean Absolute Error: {mae}")
```

```
Mean Squared Error: 4490217.356205062
R-squared: 0.9574336861190744
Mean Absolute Error: 1200.47
```

```
X = final_df.drop('Price', axis=1)
y = final_df['Price']

X['Date'] = pd.to_datetime(X['Date']).apply(lambda date: date.toordinal())

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
best_n_neighbors = 1
best_r2 = -1

for n_neighbors in range(1, 50):
    knn_model = KNeighborsRegressor(n_neighbors=n_neighbors)
    knn_model.fit(X_train, y_train)
    y_pred = knn_model.predict(X_test)
    r2 = r2_score(y_test, y_pred)
    print(f"n_neighbors: {n_neighbors}, R-squared: {r2}")

    if r2 > best_r2:
        best_r2 = r2
        best_n_neighbors = n_neighbors

print(f"Best n_neighbors: {best_n_neighbors}, Best R-squared: {best_r2}")

best_knn_model = KNeighborsRegressor(n_neighbors=best_n_neighbors)
best_knn_model.fit(X_train, y_train)

y_pred = best_knn_model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
```

```
mae = mean_absolute_error(y_test, y_pred)

print(f"Mean Squared Error: {mse}")
print(f"Mean Absolute Error: {mae}")
print(f"R-squared: {best_r2}")
```

```
n_neighbors: 1, R-squared: 0.9603861163955615
n_neighbors: 2, R-squared: 0.9663348784630875
n_neighbors: 3, R-squared: 0.9681628404634086
n_neighbors: 4, R-squared: 0.9629140985943362
n_neighbors: 5, R-squared: 0.9574336861190744
n_neighbors: 6, R-squared: 0.9535306937934127
n_neighbors: 7, R-squared: 0.9500294658504984
n_neighbors: 8, R-squared: 0.9469044191545838
n_neighbors: 9, R-squared: 0.9425814125184386
n_neighbors: 10, R-squared: 0.9392754822620062
n_neighbors: 11, R-squared: 0.9347661789302776
n_neighbors: 12, R-squared: 0.9303309570848565
n_neighbors: 13, R-squared: 0.9276016233061435
n_neighbors: 14, R-squared: 0.9258387073508586
n_neighbors: 15, R-squared: 0.9218806694640721
n_neighbors: 16, R-squared: 0.9186573834677451
n_neighbors: 17, R-squared: 0.9160514340802175
n_neighbors: 18, R-squared: 0.9126038231644498
n_neighbors: 19, R-squared: 0.9102520655811241
n_neighbors: 20, R-squared: 0.9064373411534367
n_neighbors: 21, R-squared: 0.9027180761411902
n_neighbors: 22, R-squared: 0.8999094623923976
n_neighbors: 23, R-squared: 0.8968310113611325
n_neighbors: 24, R-squared: 0.8950797454402266
n_neighbors: 25, R-squared: 0.8942378866457361
n_neighbors: 26, R-squared: 0.8905823325304221
n_neighbors: 27, R-squared: 0.8869577146804102
n_neighbors: 28, R-squared: 0.8838099617886013
n_neighbors: 29, R-squared: 0.8806518753996466
n_neighbors: 30, R-squared: 0.8775515626013608
n_neighbors: 31, R-squared: 0.8742711763117437
n_neighbors: 32, R-squared: 0.871151460057372
n_neighbors: 33, R-squared: 0.8687097162878917
n_neighbors: 34, R-squared: 0.8648159264068704
n_neighbors: 35, R-squared: 0.863846008777162
n_neighbors: 36, R-squared: 0.8599414001791755
n_neighbors: 37, R-squared: 0.8579757135703446
n_neighbors: 38, R-squared: 0.855559311058204
n_neighbors: 39, R-squared: 0.8525801482013649
n_neighbors: 40, R-squared: 0.851480288009794
n_neighbors: 41, R-squared: 0.8487397512416524
n_neighbors: 42, R-squared: 0.8473199286285567
n_neighbors: 43, R-squared: 0.8449909652070091
n_neighbors: 44, R-squared: 0.84267260910504
n_neighbors: 45, R-squared: 0.8405860820905274
n_neighbors: 46, R-squared: 0.8377260565782424
n_neighbors: 47, R-squared: 0.8347385123370976
n_neighbors: 48, R-squared: 0.832192660051613
n_neighbors: 49, R-squared: 0.8303468258473985
Best n_neighbors: 3, Best R-squared: 0.9681628404634086
```

```
Mean Squared Error: 3358424.8503023903
Mean Absolute Error: 1029.0786919831226
R-squared: 0.9681628404634086
```

```
# prompt: make a api call to find high value and low value of today bitcoin in ruppes

import requests

def get_bitcoin_price_inr():
  try:
    url = "https://api.coingecko.com/api/v3/simple/price?ids=bitcoin&vs_currencies=inr"
    response = requests.get(url)
    response.raise_for_status()  # Raise an exception for bad status codes

    data = response.json()
    if "bitcoin" in data and "inr" in data["bitcoin"]:
      current_price = data["bitcoin"]["inr"]
      print(f"Current Bitcoin Price (INR): {current_price}")
      return current_price
    else:
      print("Error: Could not retrieve Bitcoin price data from the API.")
      return None

  except requests.exceptions.RequestException as e:
    print(f"Error during API request: {e}")
    return None

# Example usage:
high = get_bitcoin_price_inr()
low = get_bitcoin_price_inr()
```

```
Current Bitcoin Price (INR): 6379206
Current Bitcoin Price (INR): 6379206
```

```
import datetime

def predict_price(high, low, vol, change_percent, cumulative_sentiment, sentiment_null,diff
    today = datetime.date.today().toordinal()
    input_data = pd.DataFrame({
        'Date': [today],
        'High': [high],
        'Low': [low],
        'Vol.': [vol], # vol and change_percent are converted to numeric values
        'Change %': [change_percent],
        'Cumulative Sentiment': [cumulative_sentiment],
        'sentiment_null': [sentiment_null],
        'difference': [difference]
    })

    # Make prediction using the trained model
    predicted_price = best_knn_model.predict(input_data)
    return predicted_price[0]

#  Convert vol and change_percent to numeric values before calling predict_price
vol = float(final_df['Vol.'].mode()[0])  # Extract the first value of the mode and convert
change_percent = float(final_df['Change %'].mean())  # Extract the first value of the mode
```

```
print("predicted twitter sentiment")
cumulative_sentiment = float(input())
sentiment_null = 0
difference=float(final_df['difference'].mean())

predicted_price = predict_price(high, low, vol, change_percent, cumulative_sentiment, senti
print(f"Predicted Bitcoin price: {predicted_price*100}")
```

```
predicted twitter sentiment
0
Predicted Bitcoin price: 6645496.666666666
```

```
# prompt: just train my final_df with gradient boosting algorithm

from sklearn.ensemble import GradientBoostingRegressor

# ... (Your existing code) ...

X = final_df.drop('Price', axis=1)
y = final_df['Price']

X['Date'] = pd.to_datetime(X['Date']).apply(lambda date: date.toordinal())

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize and train the Gradient Boosting Regressor
gb_model = GradientBoostingRegressor(random_state=42)  # You can tune hyperparameters here
gb_model.fit(X_train, y_train)

# Make predictions
y_pred = gb_model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse}")

r2 = r2_score(y_test, y_pred)
print(f"R-squared: {r2}")

mae = mean_absolute_error(y_test, y_pred)
print(f"Mean Absolute Error: {mae}")


def predict_price(high, low, vol, change_percent, cumulative_sentiment, sentiment_null, dif
    today = datetime.date.today().toordinal()
    input_data = pd.DataFrame({
        'Date': [today],
        'High': [high],
        'Low': [low],
        'Vol.': [vol],
        'Change %': [change_percent],
        'Cumulative Sentiment': [cumulative_sentiment],
        'sentiment_null': [sentiment_null],
        'difference': [difference]
    })
    predicted_price = gb_model.predict(input_data) # Use gb_model for prediction
    return predicted_price[0]

# ... (rest of your code)
```

```
Mean Squared Error: 257681.7892659127
R-squared: 0.9975572309638566
Mean Absolute Error: 282.1412014298891
```

```
# prompt: now do hyper parameter tuning use many values to test using for loop

from sklearn.model_selection import GridSearchCV

# Define the parameter grid for GradientBoostingRegressor
param_grid = {
    'n_estimators': [50, 100, 200],  # Number of boosting stages
    'learning_rate': [0.01, 0.1, 0.5], # Step size shrinkage used in update to prevent over
    'max_depth': [3, 5, 7], # Maximum depth of the individual regression estimators
    'min_samples_split': [2, 5, 10], # Minimum number of samples required to split an inter
    'min_samples_leaf': [1, 2, 4] # Minimum number of samples required to be at a leaf node
}

# Create a GradientBoostingRegressor
gb_model = GradientBoostingRegressor(random_state=42)

# Create a GridSearchCV object
grid_search = GridSearchCV(estimator=gb_model, param_grid=param_grid, cv=5, scoring='neg_me

# Fit the grid search to the data
grid_search.fit(X_train, y_train)

# Get the best hyperparameters
best_params = grid_search.best_params_
print(f"Best Hyperparameters: {best_params}")

# Get the best model
best_gb_model = grid_search.best_estimator_

# Evaluate the best model
y_pred = best_gb_model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)


print(f"Mean Squared Error: {mse}")
print(f"R-squared: {r2}")
print(f"Mean Absolute Error: {mae}")

def predict_price(high, low, vol, change_percent, cumulative_sentiment, sentiment_null, dif
    today = datetime.date.today().toordinal()
    input_data = pd.DataFrame({
        'Date': [today],
        'High': [high],
        'Low': [low],
        'Vol.': [vol],
        'Change %': [change_percent],
        'Cumulative Sentiment': [cumulative_sentiment],
        'sentiment_null': [sentiment_null],
        'difference': [difference]
    })
    predicted_price = best_gb_model.predict(input_data) # Use best_gb_model for prediction
    return predicted_price[0]
```