

▼ Datasets

```
1 #Price
```

```
1 import pandas as pd
2
3 # URL to the raw CSV file
4 url = 'https://raw.githubusercontent.com/Amarpreet3/CIND-820-CAPSTONE/main/Sentimental%20Analysis/BitcoinPricePreprocessed.csv'
5
6 # Read the CSV file from the URL
7 crypto_usd = pd.read_csv(url)
8
9 # Display the first few rows of the data
10 print(crypto_usd.head())
11
12
```

	time	close	high	low	open	volume	from \
0	2023-02-19 13:00:00	24682.03	24715.82	24682.03	24707.39	903.97	
1	2023-02-19 14:00:00	24765.79	24792.85	24679.21	24682.03	1220.29	
2	2023-02-19 15:00:00	24928.21	25022.49	24751.96	24765.79	5074.50	
3	2023-02-19 16:00:00	24786.44	25175.28	24704.53	24928.21	7094.72	
4	2023-02-19 17:00:00	24364.95	24806.64	24346.17	24786.44	6896.84	

	volumeto	Date	Time	volume	marketcap	price_delta
0	2.233594e+07	2023-02-19	13:00:00	2.233504e+07	5.512964e+11	NaN
1	3.020300e+07	2023-02-19	14:00:00	3.020178e+07	7.480012e+11	83.76
2	1.263085e+08	2023-02-19	15:00:00	1.263034e+08	3.148644e+12	162.42
3	1.770671e+08	2023-02-19	16:00:00	1.770600e+08	4.388863e+12	-141.77
4	1.693379e+08	2023-02-19	17:00:00	1.693310e+08	4.125910e+12	-421.49

```
1 import pandas as pd
2
3 file_urls = [
4     'https://raw.githubusercontent.com/Amarpreet3/CIND-820-CAPSTONE/main/Sentimental%20Analysis/BitcoinTweetsPreprocessed_1.csv',
5     'https://raw.githubusercontent.com/Amarpreet3/CIND-820-CAPSTONE/main/Sentimental%20Analysis/BitcoinTweetsPreprocessed_2.csv',
6     'https://github.com/Amarpreet3/CIND-820-CAPSTONE/raw/main/Sentimental%20Analysis/BitcoinTweetsPreprocessed_3.csv',
7     'https://github.com/Amarpreet3/CIND-820-CAPSTONE/raw/main/Sentimental%20Analysis/BitcoinTweetsPreprocessed_4.csv',
8     'https://github.com/Amarpreet3/CIND-820-CAPSTONE/raw/main/Sentimental%20Analysis/BitcoinTweetsPreprocessed_5.csv',
9     'https://github.com/Amarpreet3/CIND-820-CAPSTONE/raw/main/Sentimental%20Analysis/BitcoinTweetsPreprocessed_6.csv'
10 ]
11
12 dfs = []
13
14 for url in file_urls:
15     # Read the CSV file
16     df = pd.read_csv(url)
17
18     # Append the DataFrame to the list
19     dfs.append(df)
20
21 # Combine all DataFrames into a single DataFrame
22 combined_df = pd.concat(dfs)
23
24 # Display the first few rows of the combined DataFrame
25 print(combined_df.head())
26
```

	user_name	user_location	\
0	Irk	Vancouver, WA	
1	Xiang Zhang	NaN	
2	Rhizoo	NaN	
3	Hari Marquez	Las Vegas, NV	
4	Bitcoin Candle Bot	Brazil	

	user_description	user_created	\
0	Irk started investing in the stock market in 1...	2018-08-11 03:17:00	
1	Professional Software Engineer 000000Crypto ...	2011-01-11 01:37:00	
2	researcher. local maxima dunning&kruger spec...	2019-04-03 18:09:00	
3	Don't trust, verify. #Bitcoin El Salvador ...	2014-01-17 23:04:00	
4	Robot that posts the closure of the bitcoin da...	2021-01-06 01:36:00	

	user_followers	user_friends	user_favourites	user_verified	\
0	116.0	8.0	4580.0	False	

```
1      42.0      22.0      5.0      False
2      778.0     627.0     32005.0    False
3      222.0     521.0     13052.0    False
4      40.0      4.0      1.0      False

      date                                     text \
0 2023-02-25 23:59:00 bitcoin btc rest crypto ye bitcoin cryptocurr ...
1 2023-02-25 23:59:00 retriev invest fund current ongo tidexcoin kic...
2 2023-02-25 23:59:00 bull save monthli thread today good shit bitco...
3 2023-02-25 23:59:00 el salvador shape futur bitcoin membv32cn
4 2023-02-25 23:59:00 candl day 25022023 close open 2319406 high 232...

      hashtags                                source \
0      ['Bitcoin', 'crypto', 'NeedsMoreCrash']  Twitter Web App
1  ['Tidexcoin', 'Kicurrency', 'LMY', 'GMK', 'SYR...  Twitter for iPhone
2      ['bitcoin']                               Twitter Web App
3      ['Bitcoin']                               Twitter Web App
4      ['Bitcoin', 'Candle', 'BearMarket']  Bitcoin Candle Bot

      is_retweet  compound      score sentiment_level  polarity  subjectivity
0      0.0      -0.4019 -2.154092e+05      Negative  0.000000      0.000000
1      0.0      0.0000  0.000000e+00      Neutral  0.000000      0.400000
2      0.0      0.3612  9.005682e+06      Positive  0.250000      0.700000
3      0.0      0.0000  0.000000e+00      Neutral  0.000000      0.000000
4      0.0      -0.2732 -2.240240e+01      Negative  0.053333      0.446667
```

```
1 tweets = combined_df.copy()

1 tweets.head()
```

	user_name	user_location	user_description	user_created	user_followers	user_friends	u:
0	Irk	Vancouver, WA	Irk started investing in the stock market in 1...	2018-08-11 03:17:00	116.0	8.0	
1	Yiang		Professional Software Engineer ðŸ’ŽðŸ’ŽðŸ’ŽCrypto ...	2011-01-11 01:37:00	42.0	22.0	
2	Rhizoo	NaN	researcher. local maxima dunningâŸ’kruger spec...	2019-04-03 18:09:00	778.0	627.0	
3	Hari Marquez	Las Vegas, NV	DonâŸ’t trust, verify. #Bitcoin El Salvador ...	2014-01-17 23:04:00	222.0	521.0	
4	Bitcoin Candle Bot	Brazil	Robot that posts the closure of the bitcoin da...	2021-01-06 01:36:00	40.0	4.0	

```
1 print(tweets.columns)

Index(['user_name', 'user_location', 'user_description', 'user_created',
      'user_followers', 'user_friends', 'user_favourites', 'user_verified',
      'date', 'text', 'hashtags', 'source', 'is_retweet', 'compound', 'score',
      'sentiment_level', 'polarity', 'subjectivity'],
      dtype='object')

1 import pandas as pd
2
3
4 # Check the shape of the dataset
5 print("Shape of the dataset:", tweets.shape)
6
7 # Check the size of the dataset
```

```
8 print("Size of the dataset (number of elements):", tweets.size)
9
```

```
Shape of the dataset: (167652, 18)
Size of the dataset (number of elements): 3017736
```

```
1 import pandas as pd
2 import os
3
4
5 # Check the shape of the data
6 print("Shape of the data:", tweets.shape)
7
8
```

```
Shape of the data: (167652, 18)
```

```
1 label_counts = tweets['sentiment_level'].value_counts()
2 print(label_counts)
```

```
Neutral          93169
Positive         35921
Extreme Positive  17343
Negative         15903
Extreme Negative   5316
Name: sentiment_level, dtype: int64
```

▼ Combining both datasets

```
1 # Create a copy of the bitcoin price DataFrame
2 crypto_usd.head(2)
```

	time	close	high	low	open	volumefrom	volumeto	Date	Time
Saved successfully!				24682.03	24707.39	903.97	22335943.28	2023-02-19	13:00:00 22

```
1 print(crypto_usd.columns)

Index(['time', 'close', 'high', 'low', 'open', 'volumefrom', 'volumeto',
      'Date', 'Time', 'volume', 'marketcap', 'price_delta'],
      dtype='object')

1 df_score = tweets.copy()
```

▼ Classification on Price Prediction based on sentiment

```
1 import pandas as pd
2 import numpy as np
3
4 # Define custom bin edges based on quantiles
5 bin_edges = np.linspace(df_score['compound'].min(), df_score['compound'].max(), num=6) # Adjust the 'num' parameter as needed
6
7 # Define labels
8 labels = ['Extreme Negative', 'Negative', 'Neutral', 'Positive', 'Extreme Positive']
9
10 # Calculate average compound score for each sentiment level
11 sentiment_scores = []
12 for i in range(len(bin_edges)-1):
13     lower_bound = bin_edges[i]
14     upper_bound = bin_edges[i+1]
15     scores_in_range = df_score[(df_score['compound'] >= lower_bound) & (df_score['compound'] < upper_bound)]['compound']
16     sentiment_scores.append(scores_in_range.mean())
17
18 # Map sentiment levels to numerical values with scores
19 sentiment_mapping = {label: score for label, score in zip(labels, sentiment_scores)}
20 df_score['sentiment_score'] = df_score['sentiment_level'].map(sentiment_mapping)
21
```

```
22 # Save the updated dataframe as a new CSV file
23 df_score.to_csv('updated_sentiment_data.csv', index=False)
24

1 # Create a copy of the bitcoin tweets DataFrame
2 df_tweets = pd.read_csv('/content/updated_sentiment_data.csv')
3 df_tweets.head(2)
```

	user_name	user_location	user_description	user_created	user_followers	user_friends	u:
0	Irk	Vancouver, WA	Irk started investing in the stock market in 1...	2018-08-11 03:17:00	116.0	8.0	
1	Xiang Zhang	NaN	Professional Software Engineer ðŸ’Ž»ðŸ’Ž»Crypto ...	2011-01-11 01:37:00	42.0	22.0	

```
1 # Merge the tweet data with the Bitcoin price data
2 tweets_df = pd.merge(df_tweets, crypto_usd, left_on='date', right_on='time', how='inner')
```

```
1 print(tweets_df.columns)
2
```

```
Index(['user_name', 'user_location', 'user_description', 'user_created',
      'user_followers', 'user_friends', 'user_favourites', 'user_verified',
      'date', 'text', 'hashtags', 'source', 'is_retweet', 'compound', 'score',
      'polarity', 'subjectivity', 'sentiment_score', 'time', 'close', 'high', 'low', 'open', 'volumefrom', 'volumeto',
      'Date', 'Time', 'volume', 'marketcap', 'price_delta'],
      dtype='object')
```

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X

```
1 tweets_df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 7898 entries, 0 to 7897
Data columns (total 31 columns):
#   Column                Non-Null Count  Dtype
---  -
0   user_name              7898 non-null   object
1   user_location          3898 non-null   object
2   user_description       7620 non-null   object
3   user_created           7898 non-null   object
4   user_followers         7898 non-null   float64
5   user_friends           7898 non-null   float64
6   user_favourites        7898 non-null   float64
7   user_verified          7898 non-null   bool
8   date                   7898 non-null   object
9   text                   7898 non-null   object
10  hashtags               7891 non-null   object
11  source                 7891 non-null   object
12  is_retweet             7891 non-null   float64
13  compound                7898 non-null   float64
14  score                  7898 non-null   float64
15  sentiment_level        7898 non-null   object
16  polarity                7898 non-null   float64
17  subjectivity           7898 non-null   float64
18  sentiment_score        7898 non-null   float64
19  time                   7898 non-null   object
20  close                  7898 non-null   float64
21  high                   7898 non-null   float64
22  low                    7898 non-null   float64
23  open                   7898 non-null   float64
24  volumefrom             7898 non-null   float64
25  volumeto               7898 non-null   float64
26  Date                   7898 non-null   object
27  Time                   7898 non-null   object
28  volume                 7898 non-null   float64
```

```

29 marketcap          7898 non-null    float64
30 price_delta         7898 non-null    float64
dtypes: bool(1), float64(18), object(12)
memory usage: 1.9+ MB

```

```

1 import pandas as pd
2 from sklearn.feature_extraction.text import CountVectorizer
3 from sklearn.model_selection import train_test_split
4 from sklearn.linear_model import LinearRegression
5 from sklearn.metrics import mean_squared_error, classification_report
6 from scipy.sparse import hstack
7
8 # Feature Extraction: Unigrams
9 unigram_vectorizer = CountVectorizer(ngram_range=(1, 1))
10 unigram_features = unigram_vectorizer.fit_transform(tweets_df['text'])
11
12 # Feature Extraction: Bigrams
13 bigram_vectorizer = CountVectorizer(ngram_range=(2, 2))
14 bigram_features = bigram_vectorizer.fit_transform(tweets_df['text'])
15
16 # Combining Features
17 combined_features = hstack([unigram_features, bigram_features])
18
19 # Additional Input Features
20 additional_features = tweets_df[['compound', 'score', 'polarity', 'subjectivity', 'sentiment_score']].values
21
22 # Concatenate Additional Features with Combined Features
23 X = hstack([combined_features, additional_features])
24
25 # Target Variable
26 y = tweets_df['close']
27
28 # Split the data into training and testing sets
29 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
30
31
32

```

Saved successfully!

```

2
3 # Print the first 10 rows of the term frequency matrix
4 print(combined_features[:10].toarray())
5

```

```

[[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]

```

```

1 from sklearn.metrics import mean_squared_error, accuracy_score, precision_score, recall_score, f1_score
2 import numpy as np
3 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
4 from scipy.sparse import hstack
5

```

▼ Linear Regression

```

1 from sklearn.linear_model import LinearRegression
2 from sklearn.metrics import mean_squared_error, accuracy_score, precision_score, recall_score, f1_score
3
4 # Train the linear regression model
5 model = LinearRegression()
6
7
8
9
10 model.fit(X_train, y_train)
11
12 # Make predictions on the test set
13 y_pred = model.predict(X_test)

```

```

6
7 # Evaluate the model
8 mse = mean_squared_error(y_test, y_pred)
9 r2 = r2_score(y_test, y_pred)
10 mae = mean_absolute_error(y_test, y_pred)
11 rmse = np.sqrt(mse)
12
13 print("Mean Squared Error:", mse)
14 print("R-squared:", r2)
15 print("Mean Absolute Error:", mae)
16 print("Root Mean Squared Error:", rmse)
17
18 # Use the trained model for future predictions
19 new_tweet = ["New tweet about Bitcoin"]
20 new_tweet_features = hstack([unigram_vectorizer.transform(new_tweet), bigram_vectorizer.transform(new_tweet), additional_features[:len(new_tweet)]])
21 predicted_close = model.predict(new_tweet_features)
22
23 print("Predicted Close Price:", predicted_close)
24

```

```

Mean Squared Error: 263642.15720830334
R-squared: -0.00027683995676786033
Mean Absolute Error: 434.52422429092474
Root Mean Squared Error: 513.460959770364
Predicted Close Price: [23131.47449878]

```

```

1 import matplotlib.pyplot as plt
2 import numpy as np
3
4 # Scatter plot
5 plt.figure(figsize=(8, 6))
6 plt.scatter(y_test, y_pred, color='blue', alpha=0.5)
7 plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red')
8 plt.xlabel('Actual Values')
9 plt.ylabel('Predicted Values')
10 plt.title('Actual vs. Predicted')
11 plt.show()

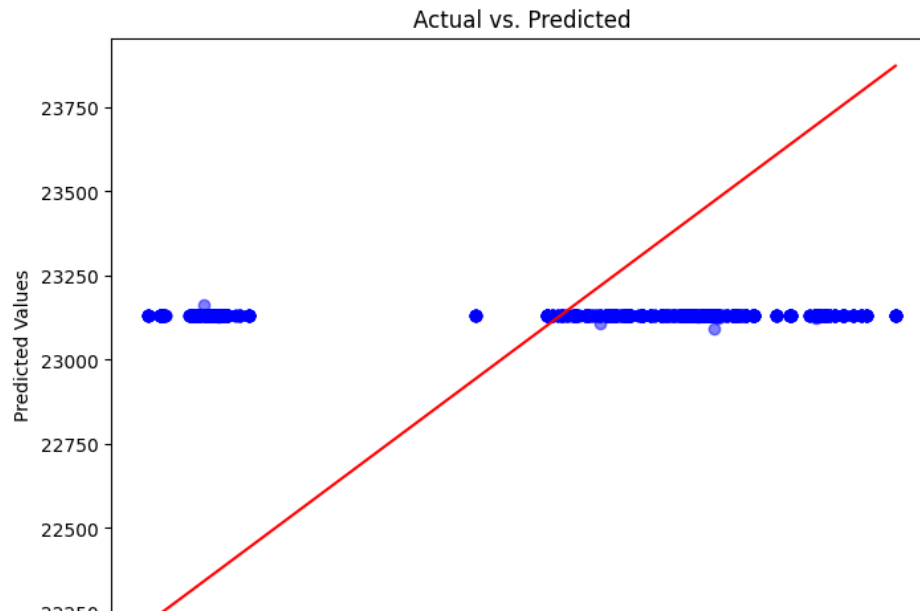
```

Saved successfully!

```

15 residuals = y_test - y_pred
16 plt.scatter(y_pred, residuals, color='blue', alpha=0.5)
17 plt.axhline(y=0, color='red', linestyle='--')
18 plt.xlabel('Predicted Values')
19 plt.ylabel('Residuals')
20 plt.title('Residual Plot')
21 plt.show()
22

```



▼ Decision Tree Regressor

```
1 from sklearn.tree import DecisionTreeRegressor
2 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
3
4 # Train the decision tree regressor model
5 model = DecisionTreeRegressor()
6
7
```

Saved successfully!

```
3 # Make predictions on the test set
4 y_pred = model.predict(X_test)
5
6 # Evaluate the model
7 mse = mean_squared_error(y_test, y_pred)
8 r2 = r2_score(y_test, y_pred)
9 mae = mean_absolute_error(y_test, y_pred)
10 rmse = np.sqrt(mse)
11 print("Model:", model)
12 print("Mean Squared Error:", mse)
13 print("R-squared:", r2)
14 print("Mean Absolute Error:", mae)
15 print("Root Mean Squared Error:", rmse)
16
17 # Use the trained model for future predictions
18 new_tweet = ["New tweet about Bitcoin"]
19 new_tweet_features = hstack([unigram_vectorizer.transform(new_tweet), bigram_vectorizer.transform(new_tweet), additional_features[:len(new_tweet)]])
20 predicted_close = model.predict(new_tweet_features)
21
22 print("Predicted Close Price:", predicted_close)
```

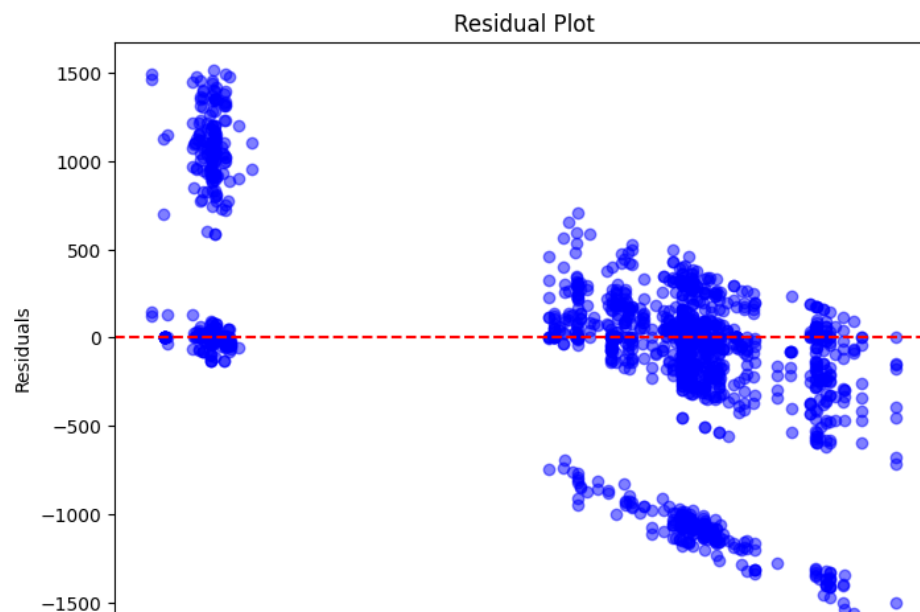
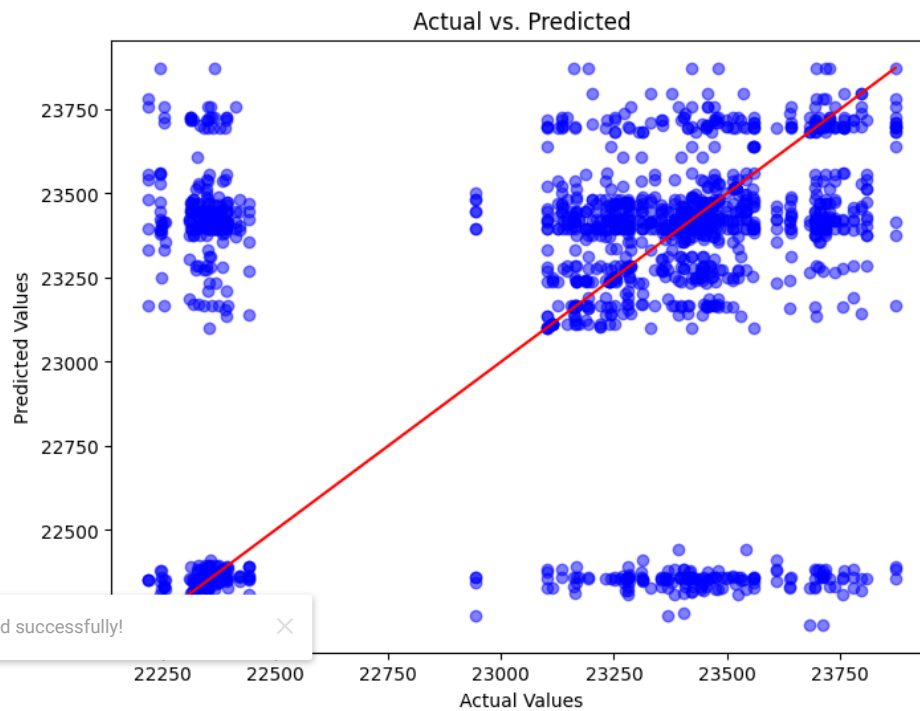
```
Model: DecisionTreeRegressor()
Mean Squared Error: 342639.9980948259
R-squared: -0.3000001902817502
Mean Absolute Error: 380.0892753164562
Root Mean Squared Error: 585.3545917602645
Predicted Close Price: [23447.51]
```

```
1 import matplotlib.pyplot as plt
2 import numpy as np
3
4 # Scatter plot
5 plt.figure(figsize=(8, 6))
6 plt.scatter(y_test, y_pred, color='blue', alpha=0.5)
7 plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red')
8 plt.xlabel('Actual Values')
```

```

9 plt.ylabel('Predicted Values')
10 plt.title('Actual vs. Predicted')
11 plt.show()
12
13 # Residual plot
14 plt.figure(figsize=(8, 6))
15 residuals = y_test - y_pred
16 plt.scatter(y_pred, residuals, color='blue', alpha=0.5)
17 plt.axhline(y=0, color='red', linestyle='--')
18 plt.xlabel('Predicted Values')
19 plt.ylabel('Residuals')
20 plt.title('Residual Plot')
21 plt.show()

```



▼ Random Forest Regressor

```

1 from sklearn.ensemble import RandomForestRegressor
2 # Rest of the code is the same as above
3 model = RandomForestRegressor()
4
5

```



```

1 model.fit(X_train, y_train)
2
3 # Make predictions on the test set
4 y_pred = model.predict(X_test)
5
6 # Evaluate the model
7 mse = mean_squared_error(y_test, y_pred)
8 r2 = r2_score(y_test, y_pred)
9 mae = mean_absolute_error(y_test, y_pred)
10 rmse = np.sqrt(mse)
11 print("Model:", model)
12 print("Mean Squared Error:", mse)
13 print("R-squared:", r2)
14 print("Mean Absolute Error:", mae)
15 print("Root Mean Squared Error:", rmse)
16
17 # Use the trained model for future predictions
18 new_tweet = ["New tweet about Bitcoin"]
19 new_tweet_features = hstack([unigram_vectorizer.transform(new_tweet), bigram_vectorizer.transform(new_tweet), additional_features[:len(new_tweet)]])
20 predicted_close = model.predict(new_tweet_features)
21
22 print("Predicted Close Price:", predicted_close)

```

```

Model: RandomForestRegressor()
Mean Squared Error: 230637.58379911553
R-squared: 0.12494482695509634
Mean Absolute Error: 333.74744294567586
Root Mean Squared Error: 480.24741935705964
Predicted Close Price: [22601.664225]

```

```

1 import matplotlib.pyplot as plt
2 import numpy as np
3
4 # Scatter plot
5 plt.figure(figsize=(8, 6))
6 plt.scatter(y_test, y_pred, color='blue', alpha=0.5)
7 plt.scatter([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red')

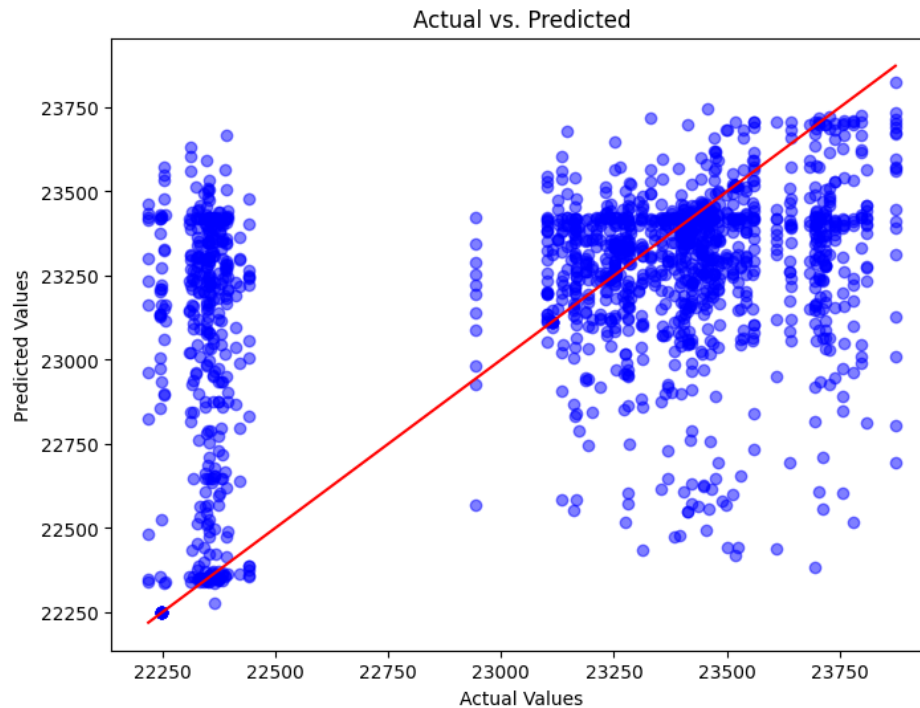
```

Saved successfully!

```

10 plt.title('Actual vs. Predicted')
11 plt.show()
12
13 # Residual plot
14 plt.figure(figsize=(8, 6))
15 residuals = y_test - y_pred
16 plt.scatter(y_pred, residuals, color='blue', alpha=0.5)
17 plt.axhline(y=0, color='red', linestyle='--')
18 plt.xlabel('Predicted Values')
19 plt.ylabel('Residuals')
20 plt.title('Residual Plot')
21 plt.show()

```



▼ Support Vector Regressor

```

1 from sklearn.svm import SVR
2
3 model = SVR()

3 # Make predictions on the test set
4 y_pred = model.predict(X_test)
5
6 # Evaluate the model
7 mse = mean_squared_error(y_test, y_pred)
8 r2 = r2_score(y_test, y_pred)
9 mae = mean_absolute_error(y_test, y_pred)
10 rmse = np.sqrt(mse)
11 print("Model:", model)
12 print("Mean Squared Error:", mse)
13 print("R-squared:", r2)
14 print("Mean Absolute Error:", mae)
15 print("Root Mean Squared Error:", rmse)
16
17 # Use the trained model for future predictions
18 new_tweet = ["New tweet about Bitcoin"]
19 new_tweet_features = hstack([unigram_vectorizer.transform(new_tweet), bigram_vectorizer.transform(new_tweet), additional_features[:len(new_tweet)]])
20 predicted_close = model.predict(new_tweet_features)
21
22 print("Predicted Close Price:", predicted_close)

Model: SVR()
Mean Squared Error: 297238.96105083235
R-squared: -0.12774547067996522
Mean Absolute Error: 399.9472665866779
Root Mean Squared Error: 545.1962592047311
Predicted Close Price: [23312.32985827]

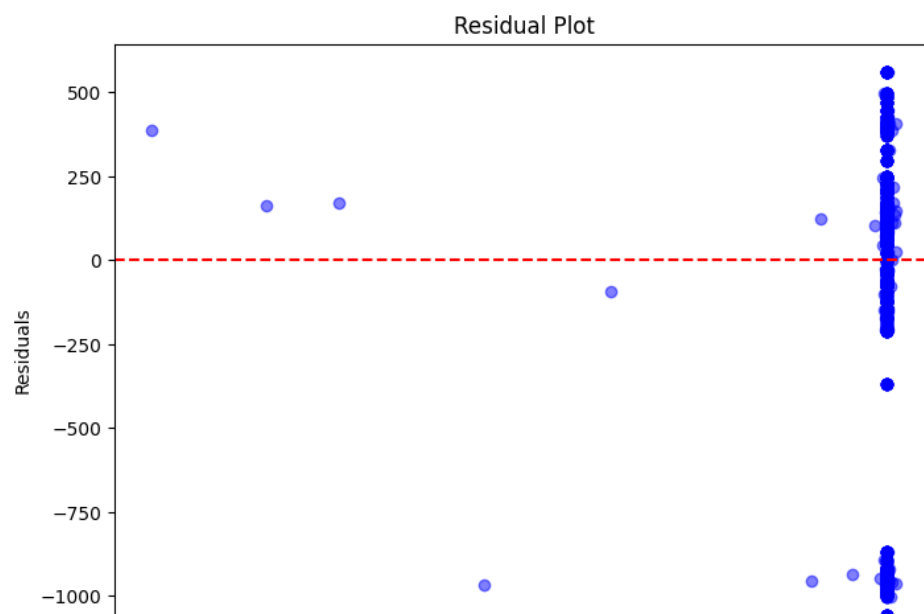
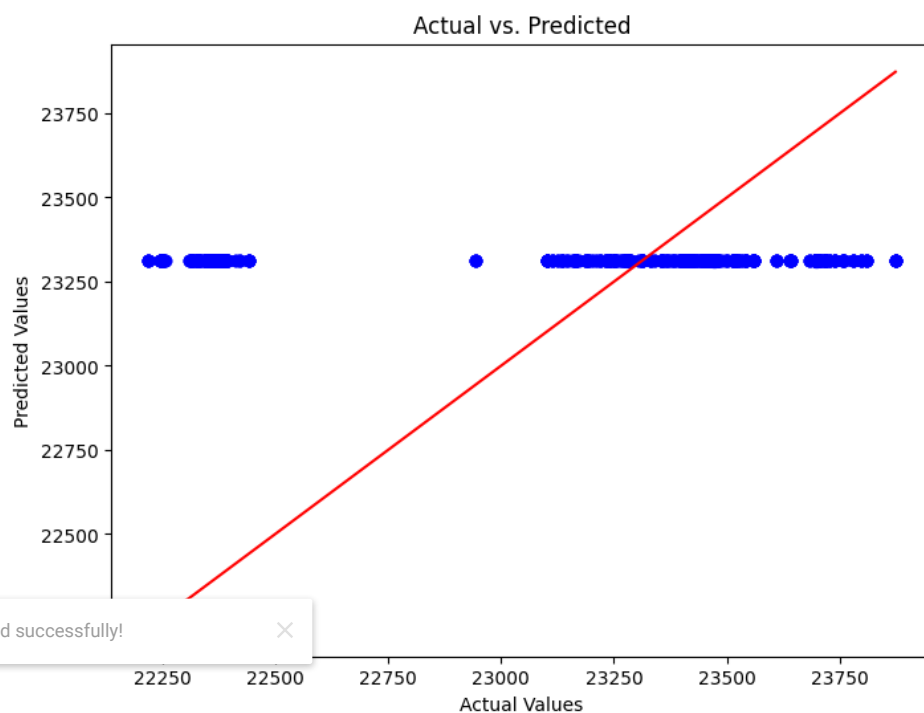
1 import matplotlib.pyplot as plt
2 import numpy as np
3
4 # Scatter plot
5 plt.figure(figsize=(8, 6))
6 plt.scatter(y_test, y_pred, color='blue', alpha=0.5)
7 plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red')
8 plt.xlabel('Actual Values')

```

```

9 plt.ylabel('Predicted Values')
10 plt.title('Actual vs. Predicted')
11 plt.show()
12
13 # Residual plot
14 plt.figure(figsize=(8, 6))
15 residuals = y_test - y_pred
16 plt.scatter(y_pred, residuals, color='blue', alpha=0.5)
17 plt.axhline(y=0, color='red', linestyle='--')
18 plt.xlabel('Predicted Values')
19 plt.ylabel('Residuals')
20 plt.title('Residual Plot')
21 plt.show()

```



▼ Gradient Boosting Regressor

```

1 from sklearn.ensemble import GradientBoostingRegressor
2
3 model = GradientBoostingRegressor()

```

```

1 model.fit(X_train, y_train)
2
3 # Make predictions on the test set
4 y_pred = model.predict(X_test)
5
6 # Evaluate the model
7 mse = mean_squared_error(y_test, y_pred)
8 r2 = r2_score(y_test, y_pred)
9 mae = mean_absolute_error(y_test, y_pred)
10 rmse = np.sqrt(mse)
11 print("Model:", model)
12 print("Mean Squared Error:", mse)
13 print("R-squared:", r2)
14 print("Mean Absolute Error:", mae)
15 print("Root Mean Squared Error:", rmse)
16
17 # Use the trained model for future predictions
18 new_tweet = ["New tweet about Bitcoin"]
19 new_tweet_features = hstack([unigram_vectorizer.transform(new_tweet), bigram_vectorizer.transform(new_tweet), additional_features[:len(new_tweet)]])
20 predicted_close = model.predict(new_tweet_features)
21
22 print("Predicted Close Price:", predicted_close)

```

```

Model: GradientBoostingRegressor()
Mean Squared Error: 218693.7380274719
R-squared: 0.17026061571930096
Mean Absolute Error: 378.0107561190105
Root Mean Squared Error: 467.6470229002553
Predicted Close Price: [23144.45192473]

```

```

1 import matplotlib.pyplot as plt
2 import numpy as np
3
4 # Scatter plot
5 plt.figure(figsize=(8, 6))
6 plt.scatter(y_test, y_pred, color='blue', alpha=0.5)
7 plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red')

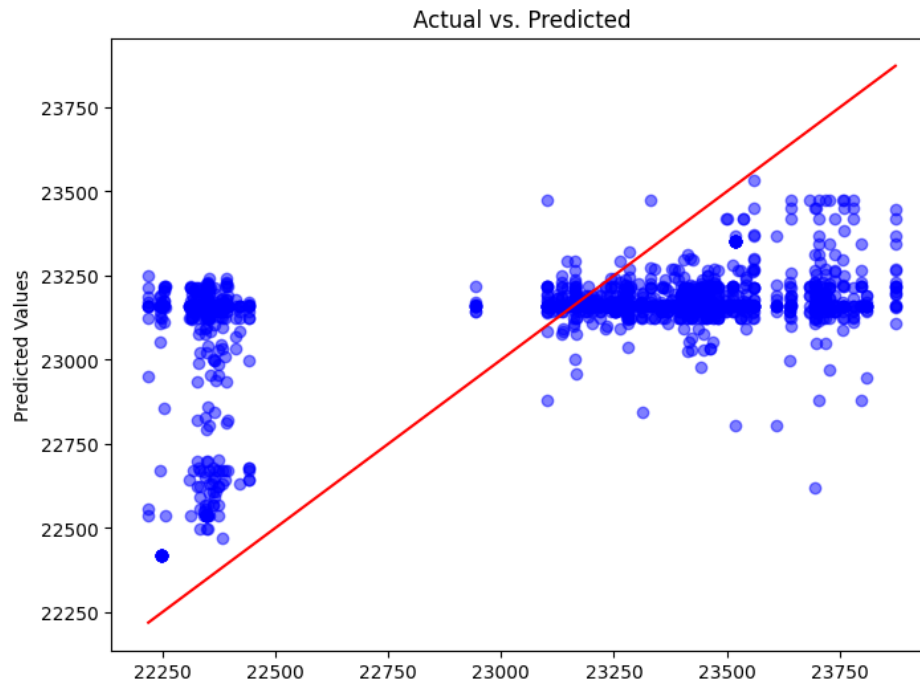
```

Saved successfully!

```

11 plt.show()
12
13 # Residual plot
14 plt.figure(figsize=(8, 6))
15 residuals = y_test - y_pred
16 plt.scatter(y_pred, residuals, color='blue', alpha=0.5)
17 plt.axhline(y=0, color='red', linestyle='--')
18 plt.xlabel('Predicted Values')
19 plt.ylabel('Residuals')
20 plt.title('Residual Plot')
21 plt.show()

```



Neural Network Regressor (MLP)

```
1 from sklearn.neural_network import MLPRegressor
2
3 model = MLPRegressor()
```

Saved successfully!

```
4 y_pred = model.predict(X_test)
5
6 # Evaluate the model
7 mse = mean_squared_error(y_test, y_pred)
8 r2 = r2_score(y_test, y_pred)
9 mae = mean_absolute_error(y_test, y_pred)
10 rmse = np.sqrt(mse)
11 print("Model:", model)
12 print("Mean Squared Error:", mse)
13 print("R-squared:", r2)
14 print("Mean Absolute Error:", mae)
15 print("Root Mean Squared Error:", rmse)
16
17 # Use the trained model for future predictions
18 new_tweet = ["New tweet about Bitcoin"]
19 new_tweet_features = hstack([unigram_vectorizer.transform(new_tweet), bigram_vectorizer.transform(new_tweet), additional_features[:len(new_tweet)]])
20 predicted_close = model.predict(new_tweet_features)
21
22 print("Predicted Close Price:", predicted_close)
```

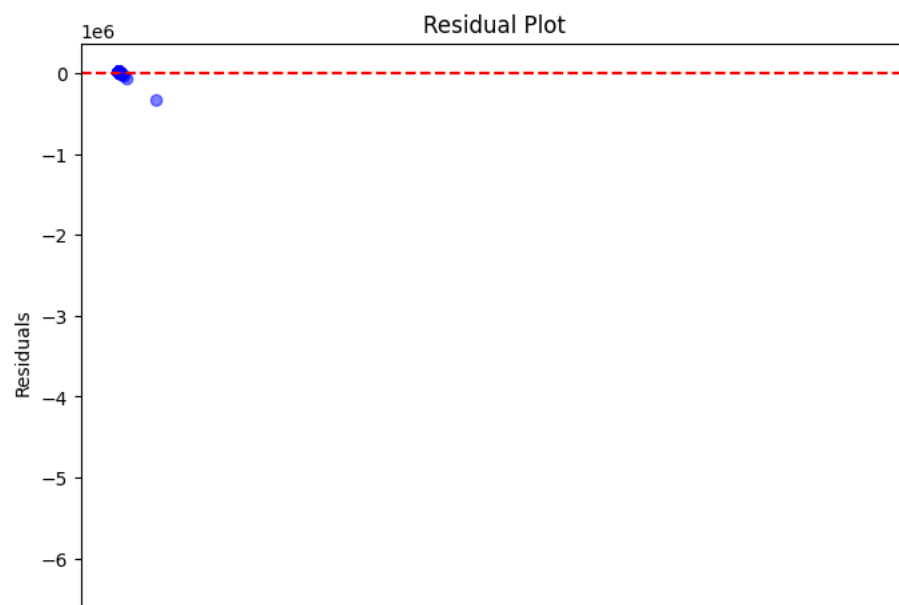
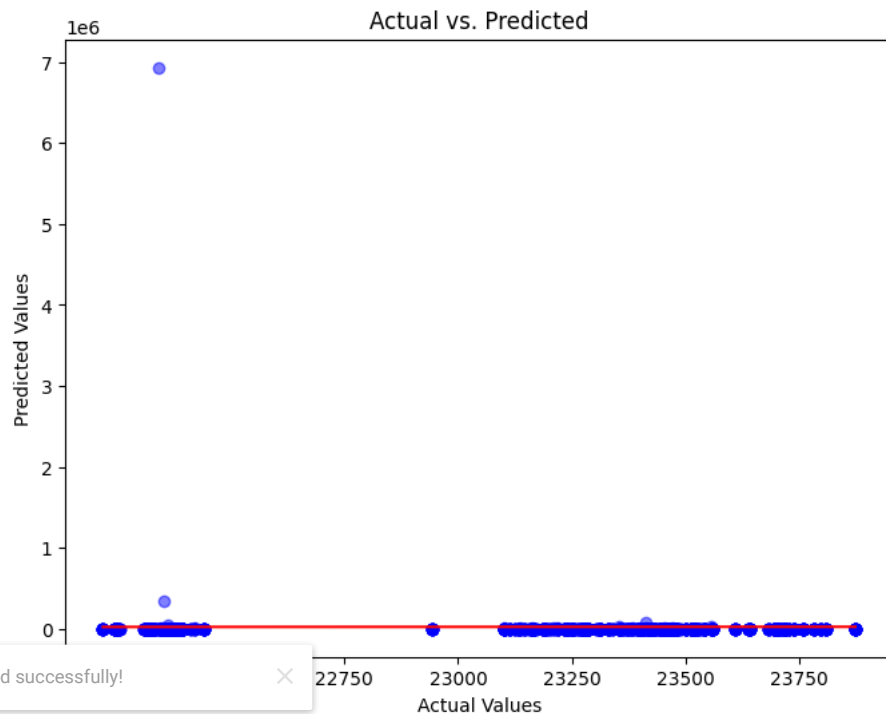
```
Model: MLPRegressor()
Mean Squared Error: 30822089613.234673
R-squared: -116940.17028040953
Mean Absolute Error: 27528.286373381194
Root Mean Squared Error: 175562.2100944126
Predicted Close Price: [3.93983228]
```

```
1 import matplotlib.pyplot as plt
2 import numpy as np
3
4 # Scatter plot
5 plt.figure(figsize=(8, 6))
6 plt.scatter(y_test, y_pred, color='blue', alpha=0.5)
7 plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red')
8 plt.xlabel('Actual Values')
9 plt.ylabel('Predicted Values')
10 plt.title('Actual vs. Predicted')
```

```

11 plt.show()
12
13 # Residual plot
14 plt.figure(figsize=(8, 6))
15 residuals = y_test - y_pred
16 plt.scatter(y_pred, residuals, color='blue', alpha=0.5)
17 plt.axhline(y=0, color='red', linestyle='--')
18 plt.xlabel('Predicted Values')
19 plt.ylabel('Residuals')
20 plt.title('Residual Plot')
21 plt.show()

```



▼ Cross Validation of Models

▼ Linear Regression

```

1 from sklearn.linear_model import LinearRegression
2 from sklearn.metrics import mean_squared_error, accuracy_score, precision_score, recall_score, f1_score
3

```

```

4 # Train the linear regression model
5 model = LinearRegression()
6

1 from sklearn.tree import DecisionTreeRegressor
2 from sklearn.model_selection import cross_val_score
3 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
4
5
6 # Perform cross-validation
7 cv_scores = cross_val_score(model, X, y, cv=5, scoring='neg_mean_squared_error')
8
9 # Convert the negative mean squared error scores to positive
10 mse_scores = -cv_scores
11
12 # Calculate the mean and standard deviation of the MSE scores
13 mean_mse = np.mean(mse_scores)
14 std_mse = np.std(mse_scores)
15
16 # Print the mean and standard deviation of the MSE scores
17 print("Mean MSE:", mean_mse)
18 print("Std MSE:", std_mse)
19

Mean MSE: 369821.0979640644
Std MSE: 306106.77056563296

```

▼ Decision Tree Regressor

```

1 from sklearn.tree import DecisionTreeRegressor
2 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
3
4 # Train the decision tree regressor model
5 model = DecisionTreeRegressor()
6
7 # Perform cross-validation
8 cv_scores = cross_val_score(model, X, y, cv=5, scoring='neg_mean_squared_error')
9
10 # Convert the negative mean squared error scores to positive
11 mse_scores = -cv_scores
12
13 # Calculate the mean and standard deviation of the MSE scores
14 mean_mse = np.mean(mse_scores)
15 std_mse = np.std(mse_scores)
16
17 # Print the mean and standard deviation of the MSE scores
18 print("Mean MSE:", mean_mse)
19 print("Std MSE:", std_mse)
20

Mean MSE: 465009.6395099891
Std MSE: 335780.0275937437

```

► Random Forest Regressor

[] ↳ 2 cells hidden

▼ Support Vector Regressor

```

1 from sklearn.svm import SVR
2
3 model = SVR()

1 from sklearn.tree import DecisionTreeRegressor
2 from sklearn.model_selection import cross_val_score
3 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
4
5
6 # Perform cross-validation
7 cv_scores = cross_val_score(model, X, y, cv=5, scoring='neg_mean_squared_error')
8
9 # Convert the negative mean squared error scores to positive
10 mse_scores = -cv_scores
11
12 # Calculate the mean and standard deviation of the MSE scores
13 mean_mse = np.mean(mse_scores)
14 std_mse = np.std(mse_scores)
15
16 # Print the mean and standard deviation of the MSE scores
17 print("Mean MSE:", mean_mse)
18 print("Std MSE:", std_mse)
19

Mean MSE: 347812.1745007644
Std MSE: 401289.31804972445

```

▼ Gradient Boosting Regressor

```

1 from sklearn.ensemble import GradientBoostingRegressor
2
3 model = GradientBoostingRegressor()

1
2
3
4
5
6 # Perform cross-validation
7 cv_scores = cross_val_score(model, X, y, cv=5, scoring='neg_mean_squared_error')
8
9 # Convert the negative mean squared error scores to positive
10 mse_scores = -cv_scores
11
12 # Calculate the mean and standard deviation of the MSE scores
13 mean_mse = np.mean(mse_scores)
14 std_mse = np.std(mse_scores)
15
16 # Print the mean and standard deviation of the MSE scores
17 print("Mean MSE:", mean_mse)
18 print("Std MSE:", std_mse)
19

Mean MSE: 348887.6854683334
Std MSE: 310402.66705840186

```

▼ Neural Network Regressor (MLP)

```

1 from sklearn.neural_network import MLPRegressor
2
3 model = MLPRegressor()

1 from sklearn.tree import DecisionTreeRegressor
2 from sklearn.model_selection import cross_val_score
3 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
4
5

```



```

6 # Perform cross-validation
7 cv_scores = cross_val_score(model, X, y, cv=5, scoring='neg_mean_squared_error')
8
9 # Convert the negative mean squared error scores to positive
10 mse_scores = -cv_scores
11
12 # Calculate the mean and standard deviation of the MSE scores
13 mean_mse = np.mean(mse_scores)
14 std_mse = np.std(mse_scores)
15
16 # Print the mean and standard deviation of the MSE scores
17 print("Mean MSE:", mean_mse)
18 print("Std MSE:", std_mse)
19
Mean MSE: 31205126756566.926
Std MSE: 47041070509094.12

```

▼ All Models Together for comparison with price [close]

```

1 import pandas as pd
2 from sklearn.feature_extraction.text import CountVectorizer
3 from sklearn.model_selection import train_test_split
4 from sklearn.linear_model import LinearRegression
5 from sklearn.metrics import mean_squared_error, classification_report
6 from scipy.sparse import hstack
7
8 # Feature Extraction: Unigrams
9 unigram_vectorizer = CountVectorizer(ngram_range=(1, 1))
10 unigram_features = unigram_vectorizer.fit_transform(tweets_df['text'])
11
12 # Feature Extraction: Bigrams
13 bigram_vectorizer = CountVectorizer(ngram_range=(2, 2))
14 bigram_features = bigram_vectorizer.fit_transform(tweets_df['text'])
15
16 combined_features = hstack([unigram_features, bigram_features])
17
18
19 # Additional Input Features
20 additional_features = tweets_df[['compound', 'score', 'polarity', 'subjectivity', 'sentiment_score']].values
21
22 # Concatenate Additional Features with Combined Features
23 X = hstack([combined_features, additional_features])
24
25 # Target Variable
26 y = tweets_df['close']
27
28 # Split the data into training and testing sets
29 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
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```

Saved successfully!

```

1 import pandas as pd
2 from sklearn.linear_model import LinearRegression
3 from sklearn.tree import DecisionTreeRegressor
4 from sklearn.ensemble import RandomForestRegressor
5 from sklearn.svm import SVR
6 from sklearn.ensemble import GradientBoostingRegressor
7 from sklearn.neural_network import MLPRegressor
8 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
9 from scipy.sparse import hstack
10
11 # Define the models
12 models = {
13     "Linear Regression": LinearRegression(),
14     "Decision Tree Regressor": DecisionTreeRegressor(),
15     "Random Forest Regressor": RandomForestRegressor(),
16     "Support Vector Regressor": SVR(),
17     "Gradient Boosting Regressor": GradientBoostingRegressor(),
18     "Neural Network Regressor": MLPRegressor()
19 }
20

```

```

21 # Initialize an empty dictionary to store the results
22 results = {}
23
24 # Iterate over the models
25 for model_name, model in models.items():
26     # Train the model
27     model.fit(X_train, y_train)
28
29     # Make predictions on the test set
30     y_pred = model.predict(X_test)
31
32     # Evaluate the model
33     mse = mean_squared_error(y_test, y_pred)
34     r2 = r2_score(y_test, y_pred)
35     mae = mean_absolute_error(y_test, y_pred)
36     rmse = np.sqrt(mse)
37
38     # Store the results in the dictionary
39     results[model_name] = {
40         "Mean Squared Error": mse,
41         "R-squared": r2,
42         "Mean Absolute Error": mae,
43         "Root Mean Squared Error": rmse
44     }
45
46     # Use the trained model for future predictions
47     new_tweet = ["New tweet about Bitcoin"]
48     new_tweet_features = hstack([unigram_vectorizer.transform(new_tweet), bigram_vectorizer.transform(new_tweet), additional_features[:ler
49     predicted_close = model.predict(new_tweet_features)
50
51     results[model_name]["Predicted Close Price"] = predicted_close
52
53 # Convert the results to a pandas DataFrame for tabular representation
54 results_df = pd.DataFrame.from_dict(results, orient="index")
55
56 # Print the results
57 print(results_df)
58

```

Saved successfully!

	Mean Squared Error	R-squared	\
Linear Regression	2.636422e+05	-2.768400e-04	
Decision Tree Regressor	3.345694e+05	-2.693799e-01	
Random Forest Regressor	2.315119e+05	1.216275e-01	
Support Vector Regressor	2.972390e+05	-1.277455e-01	
Gradient Boosting Regressor	2.188733e+05	1.695795e-01	
Neural Network Regressor	4.803038e+11	-1.822305e+06	

	Mean Absolute Error	Root Mean Squared Error	\
Linear Regression	434.524224	513.460960	
Decision Tree Regressor	374.074494	578.419766	
Random Forest Regressor	334.207529	481.156859	
Support Vector Regressor	399.947267	545.196259	
Gradient Boosting Regressor	378.111052	467.838936	
Neural Network Regressor	58711.619235	693039.555859	

	Predicted Close Price
Linear Regression	[23131.47449878233]
Decision Tree Regressor	[23447.51]
Random Forest Regressor	[22580.549866666664]
Support Vector Regressor	[23312.329858272555]
Gradient Boosting Regressor	[23144.45192472882]
Neural Network Regressor	[4.349573192223386]

```

1
2 # Transpose the DataFrame
3 transposed_df = results_df.transpose()
4
5 # Print the transposed DataFrame
6 print(transposed_df)

```

	Linear Regression	Decision Tree Regressor	\
Mean Squared Error	263642.157208	334569.425348	
R-squared	-0.000277	-0.26938	
Mean Absolute Error	434.524224	374.074494	
Root Mean Squared Error	513.46096	578.419766	
Predicted Close Price	[23131.47449878233]	[23447.51]	

	Random Forest Regressor	Support Vector Regressor	\
Mean Squared Error	231511.922529	297238.961051	

R-squared	0.121628	-0.127745
Mean Absolute Error	334.207529	399.947267
Root Mean Squared Error	481.156859	545.196259
Predicted Close Price	[22580.549866666664]	[23312.329858272555]

	Gradient Boosting Regressor	Neural Network Regressor
Mean Squared Error	218873.270426	480303825985.190186
R-squared	0.169579	-1822305.410943
Mean Absolute Error	378.111052	58711.619235
Root Mean Squared Error	467.838936	693039.555859
Predicted Close Price	[23144.45192472882]	[4.349573192223386]

1 #Linear Regression and Decision Tree Regressor have low R-squared values and high mean squared error, indicating poor fit and high predict
 2 #Random Forest Regressor and Gradient Boosting Regressor show relatively better performance with higher R-squared values, lower mean squar
 3 #The Neural Network Regressor seems to have highly inaccurate predictions, as indicated by the extremely high mean squared error and mean

1 #Based on the provided evaluation metrics, the Random Forest Regressor and Gradient Boosting Regressor perform relatively better compared

▼ All Models Together for comparison with price_delta

```

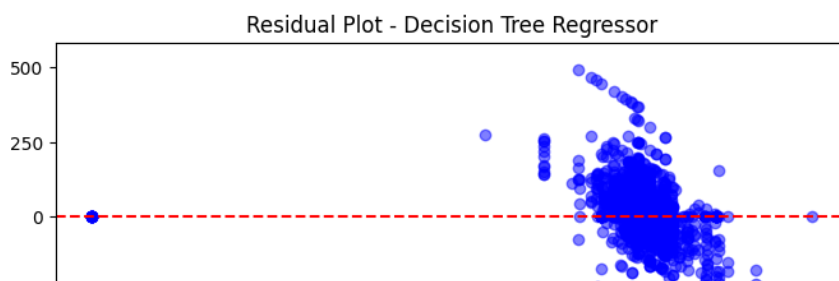
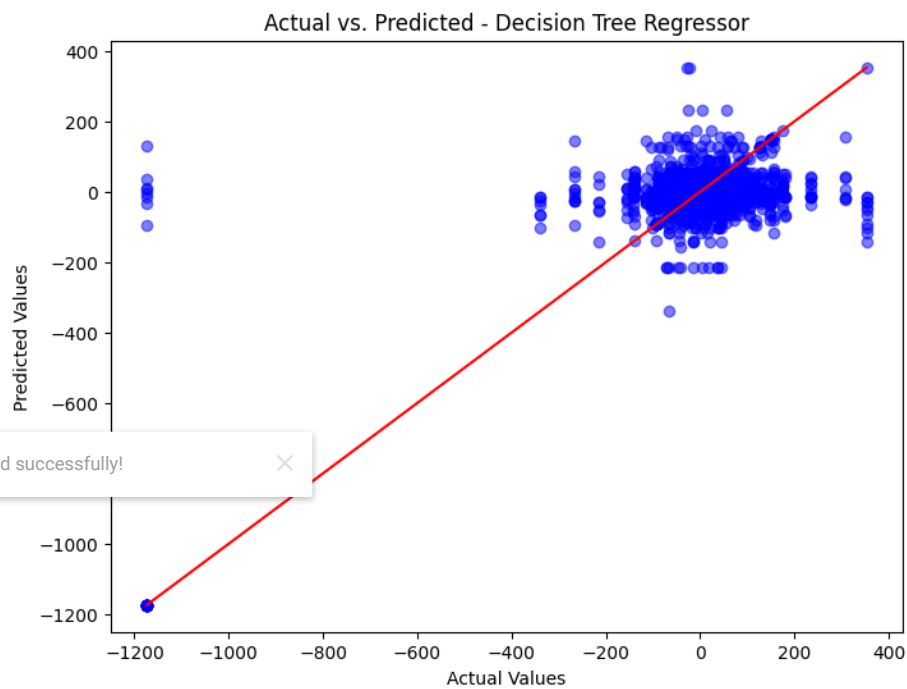
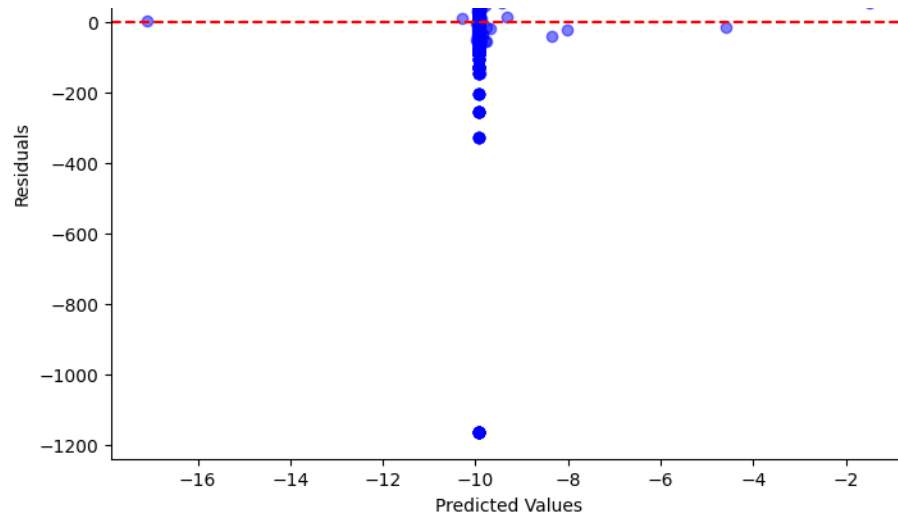
1 import pandas as pd
2 from sklearn.feature_extraction.text import CountVectorizer
3 from sklearn.model_selection import train_test_split
4 from sklearn.linear_model import LinearRegression
5 from sklearn.metrics import mean_squared_error, classification_report
6 from scipy.sparse import hstack
7
8 # Feature Extraction: Unigrams
9 unigram_vectorizer = CountVectorizer(ngram_range=(1, 1))
10 unigram_features = unigram_vectorizer.fit_transform(tweets_df['text'])
11
12 # Feature Extraction: Bigrams
13 bigram_vectorizer = CountVectorizer(ngram_range=(2, 2))
14 bigram_features = bigram_vectorizer.fit_transform(tweets_df['text'])
15
16 combined_features = hstack([unigram_features, bigram_features])
17
18
19 # Additional Input Features
20 additional_features = tweets_df[['compound', 'score', 'polarity', 'subjectivity', 'sentiment_score']].values
21
22 # Concatenate Additional Features with Combined Features
23 X = hstack([combined_features, additional_features])
24
25 # Target Variable
26 y = tweets_df['price_delta']
27
28 # Split the data into training and testing sets
29 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
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21 }
22
23 # Initialize an empty dictionary to store the results
24 results = {}
25
26 # Iterate over the models
27 for model_name, model in models.items():
28     # Train the model
29     model.fit(X_train, y_train)
30
31     # Make predictions on the test set
32     y_pred = model.predict(X_test)
33
34     # Evaluate the model
35     mse = mean_squared_error(y_test, y_pred)
36     r2 = r2_score(y_test, y_pred)
37     mae = mean_absolute_error(y_test, y_pred)
38     rmse = np.sqrt(mse)
39
40     # Store the results in the dictionary
41     results[model_name] = {
42         "Mean Squared Error": mse,
43         "R-squared": r2,
44         "Mean Absolute Error": mae,
45         "Root Mean Squared Error": rmse
46     }
47
48     # Use the trained model for future predictions
49     new_tweet = ["New tweet about Bitcoin"]
50     new_tweet_features = hstack([unigram_vectorizer.transform(new_tweet), bigram_vectorizer.transform(new_tweet), additional_features[:1]
51     predicted_close = model.predict(new_tweet_features)
52
53     results[model_name]["Predicted Close Price"] = predicted_close
54
55     # Scatter plot
56     plt.figure(figsize=(8, 6))
57     plt.scatter(y_test, y_pred, color='blue', alpha=0.5)
58     plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red')
59
60     plt.title(f'Actual vs. Predicted - {model_name}')
61     plt.show()
62
63     # Residual plot
64     plt.figure(figsize=(8, 6))
65     residuals = y_test - y_pred
66     plt.scatter(y_pred, residuals, color='blue', alpha=0.5)
67     plt.axhline(y=0, color='red', linestyle='--')
68     plt.xlabel('Predicted Values')
69     plt.ylabel('Residuals')
70     plt.title(f'Residual Plot - {model_name}')
71     plt.show()
72
73
74 # Convert the results to a pandas DataFrame for tabular representation
75 results_df = pd.DataFrame.from_dict(results, orient="index")
76
77 # Print the results
78 print(results_df)
79

```

Saved successfully!



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