Data Science Assignment: Bitcoin Market Sentiment and Trader Activity Analysis

1. Introduction

This report presents an analysis of Bitcoin market sentiment and trader activity using two datasets: the Bitcoin Market Sentiment data (Fear & Greed Index) and Historical Trader data. The objective is to explore trends within each dataset, understand the characteristics of trading behavior, and investigate the relationship between market sentiment and trading activity. The analysis covers data cleaning, exploratory data analysis, combining datasets, and drawing key insights, supported by visualizations.

2. Data Cleaning

Data cleaning was performed on both the market_sentiment and trader_data datasets to ensure data quality and prepare them for analysis.

Market Sentiment Data (market_sentiment)

- The 'date' column, initially in object format, was converted to datetime objects to enable time-series analysis.
- Rows with any missing values were removed using the dropna() function to handle incomplete data entries. The cleaned market_sentiment DataFrame has 2644 rows and 4 columns.

Trader Data (trader_data)

- The 'Timestamp IST' column, representing the trade timestamp, was converted to datetime objects using the specified format '%d-%m-%Y %H:%M' for accurate temporal analysis.
- Rows with any missing values were removed using dropna().
- A new 'date' column was extracted from the 'Timestamp IST' column to facilitate daily aggregation and merging with the market sentiment data. The cleaned trader_data DataFrame has 211224 rows and 17 columns.

3. Exploratory Data Analysis (EDA)

Exploratory data analysis was conducted on the cleaned datasets to understand their key characteristics, distributions, and initial patterns.

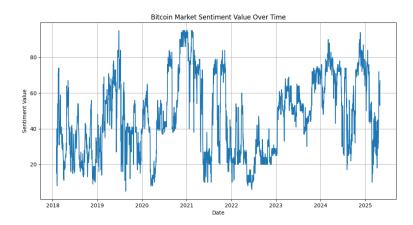
Market Sentiment Analysis

Analysis of the market_sentiment dataset focused on the sentiment 'value' and 'classification'.

Descriptive Statistics of Sentiment Value:

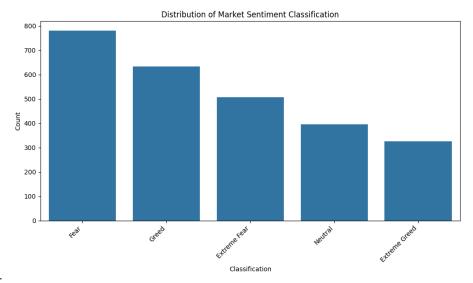
1	1	value
:	- -	:
count		2644 I
mean	-	46.9811
std	1	21.8277
min	1	5 l
25%	1	28 l
50%	1	46 l
75%	1	66 l
max		95 l

Sentiment Value Over Time: The line plot below shows the fluctuation of Bitcoin market sentiment value over the observed period, indicating the dynamic



nature of market psychology.

Distribution of Market Sentiment Classification: The count plot illustrates the frequency of each sentiment category (Extreme Fear, Fear, Neutral, Greed, Extreme Greed), providing insight into the prevailing market sentiment



over time.

Average Sentiment Value by Classification: The bar plot below shows the average sentiment value for each classification, confirming the expected progression from fear to greed.

classification		value	ı
:	-	:	
Extreme Fear	1	18.2736	١
Fear		34.1844	1
Neutral		49.9646	1
Greed		65.8468	1
Extreme Greed	Ι	82.1166	1

Trader Data Analysis

Analysis of the trader_data dataset explored trading activity, volume, and profitability.

Descriptive Statistics of Key Trading Metrics:

1	- 1	Execution Price	Size Tokens		Size USD	Closed PnL	١
:	-	:	:		:		:
coun	t	211224	211224	211224	I	211224	-
mean	.	11414.7	4623.36	5639.49	5 l	48.749	-
std		29447.7	104273	36575.1	I	919.165	-
min	- 1	4.53e-06	8.74e-07	0	I	-117990	
25%		4.8547	2.94	193.79	9 l	0	-
50%		18.28	32	597.04	45 l	0	-
75%		101.58	187.903	2058.96	6 l	5.7928	-
max	- 1	109004	1.58224e+07	3.92	2143e+06	135329	1

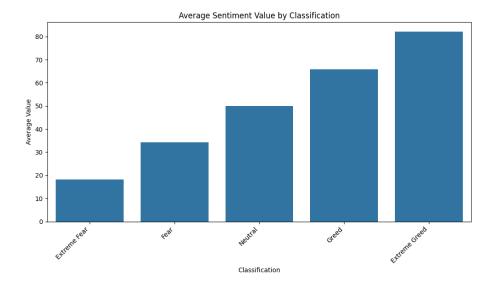
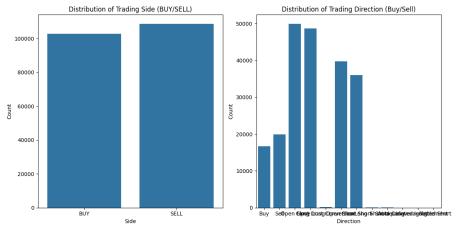
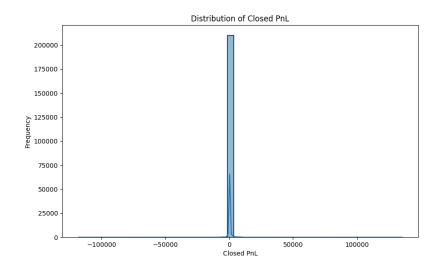


Figure 1: Average Sentiment by Classification

Distribution of Trading Side and Direction: The count plots below show the distribution of BUY/SELL trades and the corresponding trading directions.



Distribution of Closed PnL: The histogram below visualizes the distribution of profit and loss from closed trades, indicating that most trades have PnL close



to zero with some outliers.

Trading Activity by Account: Aggregating trading data by account reveals the most active and potentially most profitable traders.

Top 10 Accounts by Total Size USD:

Account	1	total_size_usd	1	average_closed_pnl
: :	- -	:	:	;
13 0x513b8629fe877bb581bf244e326a047b249c4ff1		4.20877e+08	1	68.6844
12 0x4f93fead39b70a1824f981a54d4e55b278e9f760		1.29673e+08	1	40.7405
28 0xb899e522b5715391ae1d4f137653e7906c5e2115		1.08877e+08	1	4.64831
31 0xbee1707d6b44d4d52bfe19e41f8a828645437aab		7.41078e+07		20.8063
29 0xbaaaf6571ab7d571043ff1e313a9609a10637864		6.80363e+07	1	44.3641
0 0x083384f897ee0f19899168e3b1bec365f52a9012		6.16973e+07	1	419.128
27 0xb1231a4a2dd02f2276fa3c5e2a2f3436e6bfed23		5.65436e+07	1	145.482
11 0x4acb90e786d897ecffb614dc822eb231b4ffb9f4		3.95729e+07	1	155.589
2 0x271b280974205ca63b716753467d5a371de622ab		3.38734e+07	1	-18.492
17 0x75f7eeb85dc639d5e99c78f95393aa9a5f1170d4		2.57295e+07	1	38.3196

Top 10 Accounts by Average Closed PnL (with at least 10 trades):

1 1	Account	total_size_usd	average_closed_pnl
:	:	:	
8	0x420ab45e0bd8863569a5efbb9c05d91f40624641	1.98753e+06	520.902
1 0 1	0x083384f897ee0f19899168e3b1bec365f52a9012	6.16973e+07	419.128
9	0x430f09841d65beb3f27765503d0f850b8bce7713	2.96611e+06	336.736
16	0x72c6a4624e1dffa724e6d00d64ceae698af892a0	3.05114e+06	281.826
15	0x72743ae2822edd658c0c50608fd7c5c501b2afbd	1.14745e+07	270.035
24	0xa520ded057a32086c40e7dd6ed4eb8efb82c00e0	861809	174.692
7	0x3f9a0aadc7f04a7c9d75dc1b5a6ddd6e36486cf6	1.1439e+06	161.133
11	0x4acb90e786d897ecffb614dc822eb231b4ffb9f4	3.95729e+07	155.589

-	27	0xb1231a4a2dd02f2276fa3c5e2a2f3436e6bfed23	5.65436e+07
- 1	25	0xae5eacaf9c6b9111fd53034a602c192a04e082ed	1.67743e+06

145.482 120.507

Trading Activity by Coin: Aggregating trading data by coin highlights the most traded and potentially most profitable cryptocurrencies.

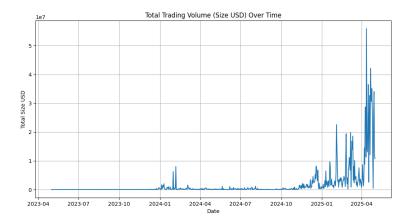
Top 10 Coins by Total Size USD:

-	Coin	1	total_size_usd	average_closed_pnl	1	number_of_trades
-	: :	- -	:		: -	:
	105 BTC		6.44232e+08	33.3044	1	26064
	137 HYPE		1.4199e+08	28.6521	1	68005
	205 SOL		1.25075e+08	153.359	1	10691
	120 ETH		1.18281e+08	118.299	1	11158
	4 @107		5.57609e+07	92.8218	1	29992
	122 FARTCOIN		8.31139e+06	-21.6532	1	4650
	210 SUI		7.78117e+06	100.692	1	1979
	217 TRUMP		7.34935e+06	-190.013	1	1920
	161 MELANIA	-	7.04071e+06	88.1552	1	4428
	233 XRP		5.34321e+06	2.11776	-	1774

Top 10 Coins by Average Closed PnL (with at least 10 trades):

-	Coin	1	total_size_usd	- 1	average_closed_pnl	number_of_trades	١
-	: :	-		: -	:	:	١
-	5 @109	1	5670.66	-	270.704	20	١
-	92 AVAX	1	400115	-	239.096	202	١
-	117 ENA	1	1.6254e+06	-	219.525	990	١
-	72 @85	1	49034.5	-	200.804	132	١
-	116 EIGEN	1	417782	-	197.063	330	١
-	112 DOGE	1	2.4521e+06	-	178.624	826	١
-	205 SOL	1	1.25075e+08	-	153.359	10691	١
-	168 MOODENG	1	161956	-	151.097	107	l
-	240 ZRO	1	1.21383e+06	-	148.328	1239	l
- 1	121 ETHFT	ı	769716	- 1	141.251 l	311	ı

Trading Activity Over Time: The line plots below show the trends in total trading volume (Size USD) and the number of trades over time.



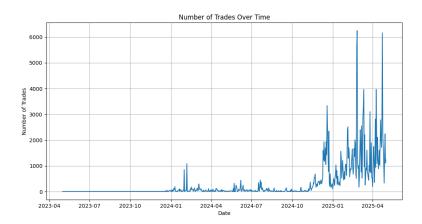


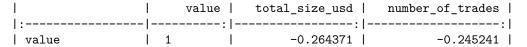
Figure 2: Number of Trades Over Time

4. Combined Data Analysis

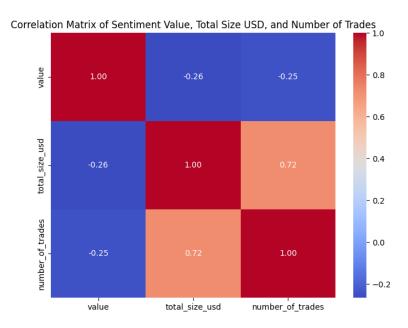
To explore the relationship between market sentiment and trading behavior, the daily trading activity data was merged with the market sentiment data based on date.

Correlation Analysis: A correlation analysis was performed between sentiment value, total trading volume, and the number of trades.

Correlation Matrix:

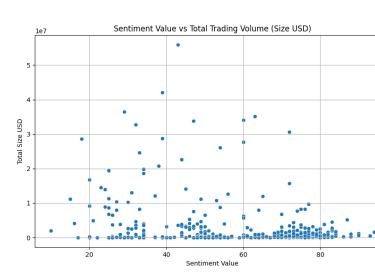


The heatmap below visualizes the correlation matrix, showing the strength and



direction of linear relationships.

Relationship between Sentiment Value and Trading Activity: The scatter plots below show the relationship between sentiment value and both total



trading volume and the number of trades.

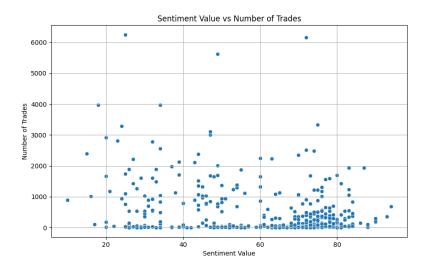
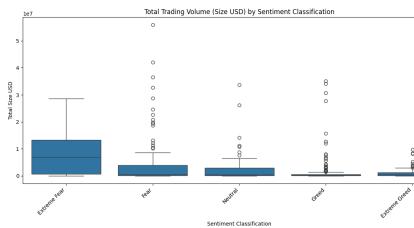


Figure 3: Sentiment vs Trades Scatterplot

Trading Activity by Sentiment Classification: The box plots below illustrate the distribution of total trading volume and the number of trades across dif-



ferent market sentiment classifications.

5. Insights

Based on the analysis of the individual and combined datasets, the following key insights were drawn: - **Sentiment Volatility:** Bitcoin market sentiment, as measured by the fear/greed index, is highly volatile and changes frequently, moving between states of extreme fear and extreme greed. - **Weak Sentiment-Activity Relationship:** Contrary to a simple assumption that higher senti-

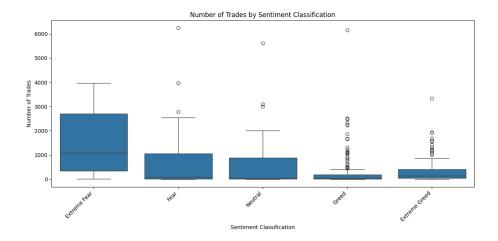


Figure 4: Trades by Sentiment Boxplot

ment leads to increased trading, the analysis revealed a weak negative correlation between market sentiment value and both total trading volume and the number of trades in this dataset. This suggests that while sentiment may play a role, it is not the primary driver of trading volume or frequency, or its influence is complex and non-linear. - Concentration of Activity and Profitability: Trading activity and profitability are not uniformly distributed across all accounts and coins. A relatively small number of accounts contribute a large portion of the total trading volume, and profitability varies significantly among both accounts and cryptocurrencies. - PnL Distribution: The distribution of Closed PnL indicates that the majority of trades result in small gains or losses, with a few outlier trades accounting for significant profits or losses. - Importance of Other Factors: The weak sentiment-activity correlation highlights the likely importance of investigating other potential drivers of trading behavior, such as price volatility, major news events, specific coin developments, and individual trader strategies.

6. Conclusion

This analysis provided valuable insights into the dynamics of Bitcoin market sentiment and trader activity based on the provided datasets. While market sentiment is highly volatile, its direct linear relationship with overall trading volume and frequency appears to be weak and even slightly inverse in this dataset. This suggests that a simple sentiment-driven trading strategy based solely on the fear/greed index may not be sufficient, and other market factors and individual strategies play significant roles. Further research could explore the impact of price changes, volatility, and specific events on trading behavior, as well as delve deeper into the strategies of highly profitable accounts.

7. References

- Bitcoin Market Sentiment Dataset (Source: Provided via gdown link)
- Historical Trader Data (Source: Provided via gdown link)
- Python libraries: pandas, numpy, matplotlib, seaborn