Bitcoin Market Sentiment & Trader Performance Analysis

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notebook_1.ipynb

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1. Introduction

This project explores the relationship between Bitcoin market sentiment and trader performance. Using two datasets — the Bitcoin Market Sentiment Dataset and Historical Trader Data from Hyperliquid — the objective was to uncover how different market emotions such as Fear, Greed, and Neutral sentiment impact trading behavior and profitability. The insights gained aim to support smarter trading strategies.

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2. Data Description

- **Bitcoin Market Sentiment Dataset:** Contains daily sentiment classifications such as Fear, Greed, Extreme Fear, Extreme Greed, and Neutral with associated sentiment scores.
- **Historical Trader Data:** Contains detailed trade information, including account ID, coin symbol, execution price, trade size, trade side (buy/sell), timestamps, closed profit and loss (PnL), fees, and more.

Preprocessing:

- Missing values were handled by removing or imputing where appropriate.

```
# Missing values
merged_df.isnull().sum().sort_values(ascending=False)
```

	0
PnL_per_USD	7
classification	6
value	6
timestamp	6
Timestamp	1
Account	0
Side	0
Size USD	0
Size Tokens	0
Execution Price	0
Coin	0
Timestamp IST	0
Direction	0
Start Position	0
Fee	0
Crossed	0
Order ID	0
Transaction Hash	0
Closed PnL	0
Trade ID	0
date	0
is_profit	0

dtype: int64

```
merged_df = merged_df.dropna(subset=['classification', 'value','timestamp','PnL_per_USD'])
```

- Duplicated Values were handled.

```python
# Duplicate
merged_df.duplicated().sum()
```

```
np.int64(0)
```

```python
merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 41747 entries, 0 to 41759
Data columns (total 22 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Account           41747 non-null  object
 1   Coin              41747 non-null  object
 2   Execution Price   41747 non-null  float64
 3   Size Tokens       41747 non-null  float64
 4   Size USD          41747 non-null  float64
 5   Side              41747 non-null  object
 6   Timestamp IST     41747 non-null  datetime64[ns]
 7   Start Position    41747 non-null  float64
 8   Direction         41747 non-null  object
 9   Closed PnL        41747 non-null  float64
 10  Transaction Hash  41747 non-null  object
 11  Order ID          41747 non-null  int64
 12  Crossed           41747 non-null  bool
 13  Fee               41747 non-null  float64
 14  Trade ID          41747 non-null  object
 15  Timestamp         41746 non-null  float64
 16  date              41747 non-null  object
 17  timestamp         41747 non-null  float64
 18  value             41747 non-null  float64
 19  classification    41747 non-null  object
 20  PnL_per_USD       41747 non-null  float64
 21  is_profit         41747 non-null  bool
dtypes: bool(2), datetime64[ns](1), float64(10), int64(1), object(8)
memory usage: 6.8+ MB
```

Describe-merged_df.describe() analysis:

Summary of Key Features:

Execution Price:

Very wide range, from near zero (~0.00001) to over 108,000, with a high standard deviation (42,575), indicating highly varied trade prices.

Size Tokens & Size USD:

Large variance in trade size and value, with some extremely large trades (up to millions in USD).

Timestamp IST:

Data covers dates from late 2023 through mid-2025.

Start Position:

Huge spread in starting positions (from -14.3 million to +11.5 million), likely representing major traders or "whales."

Closed PnL:

Profit and loss range from heavy losses (~ -117,990) to large gains (~135,329), with a very high standard deviation (1,563), indicating volatile profits/losses.

Fee:

Fees mostly small but can be negative (rebates) or extremely high (up to 837).

Value (Sentiment Score):

Ranges from 10 to 94, averaging about 55, showing a balanced spread of market sentiment.

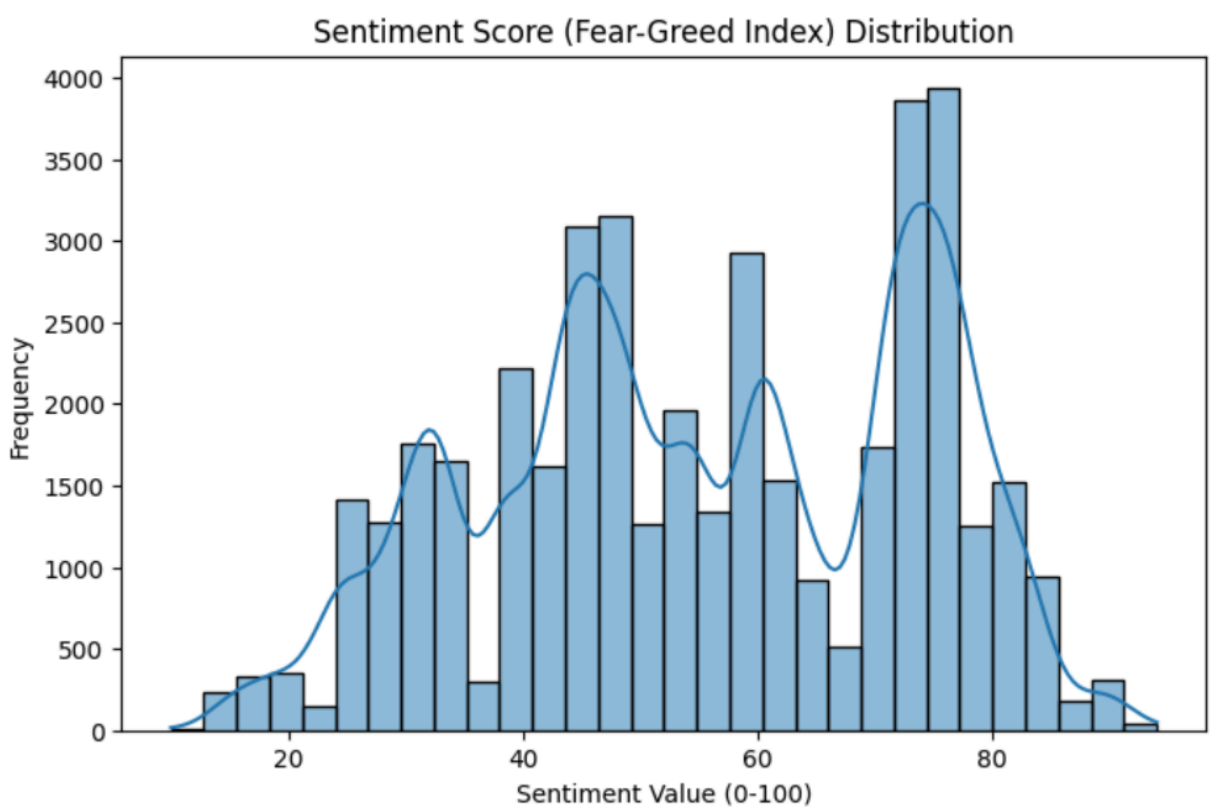
PnL_per_USD:

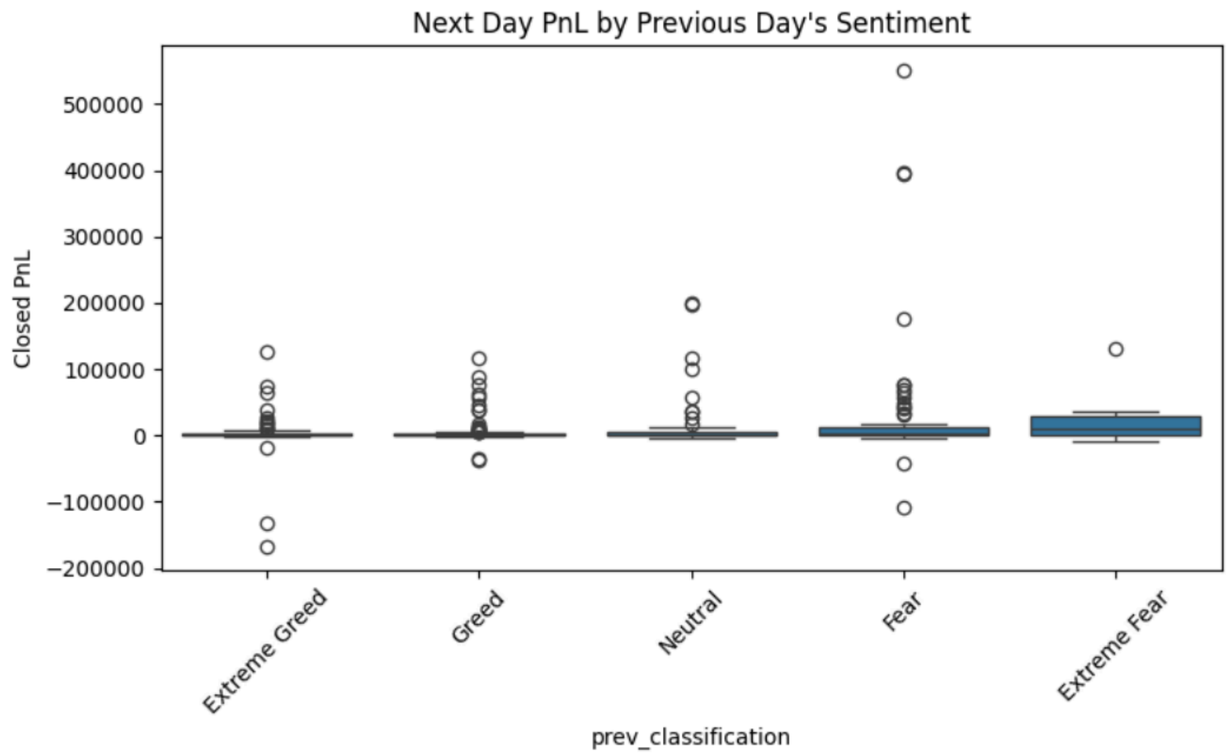
Small average returns per USD traded, with some outliers.

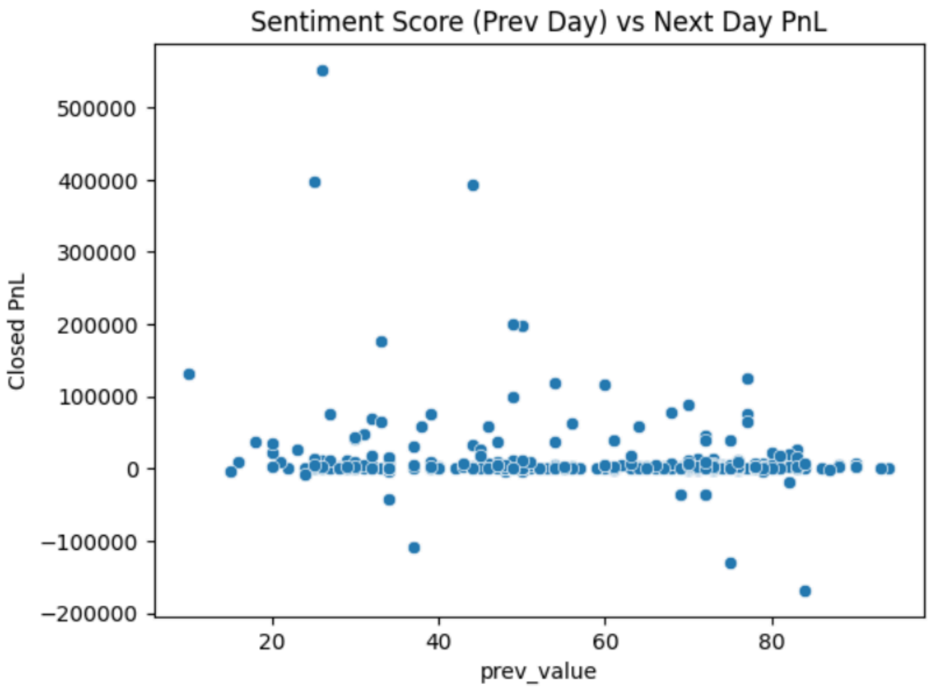
3. Exploratory Data Analysis (EDA)

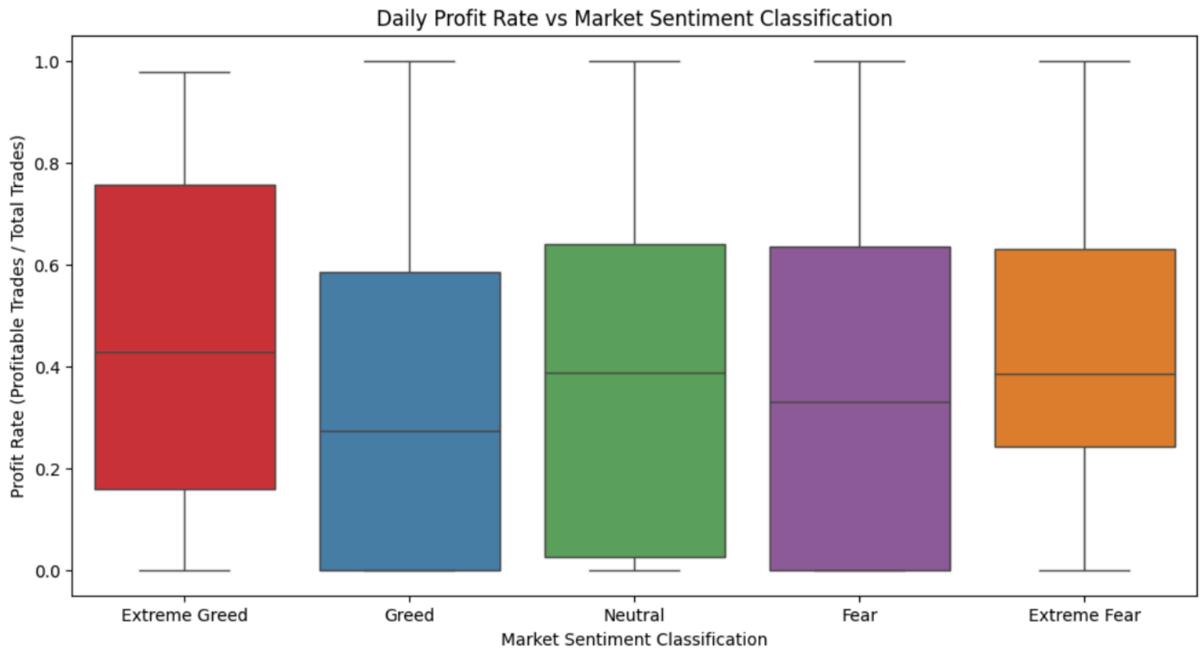
- The sentiment scores showed a wide distribution, with Extreme Fear and Extreme Greed as the most volatile states.
- Trading volume and fees varied significantly across different sentiment classifications.
- Profitable trades were most frequent during Extreme Greed days, with profitability rates of approximately 53%.
- A notable lag effect was found where previous day's sentiment influenced next day's profit outcomes.

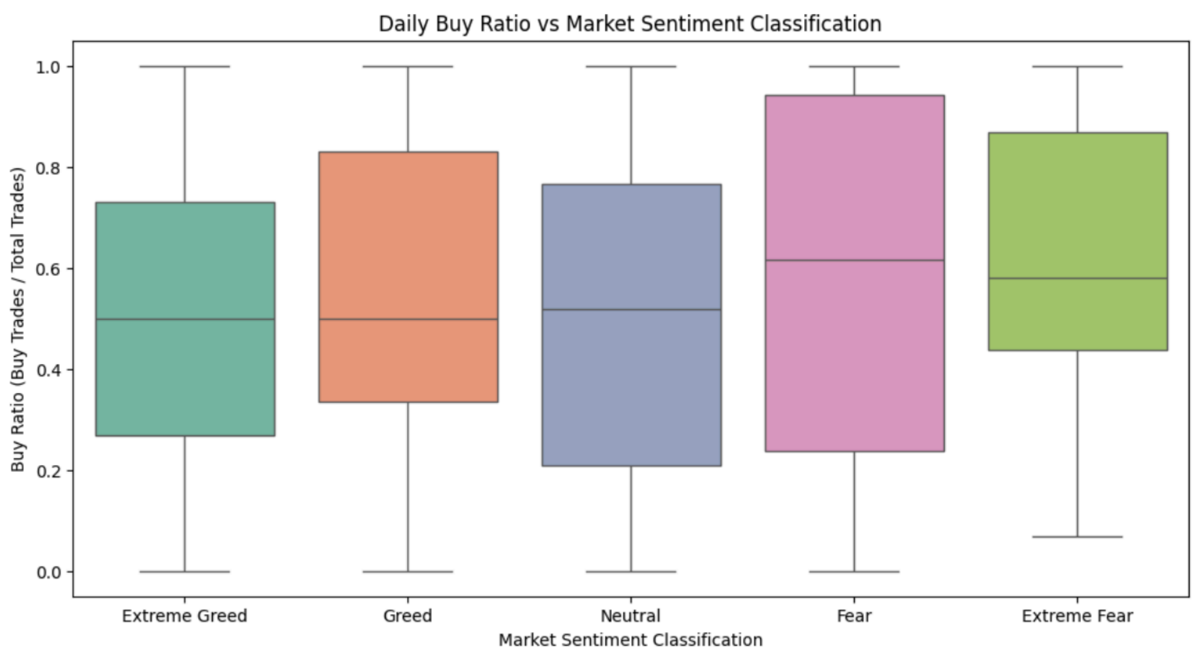
Visuals:

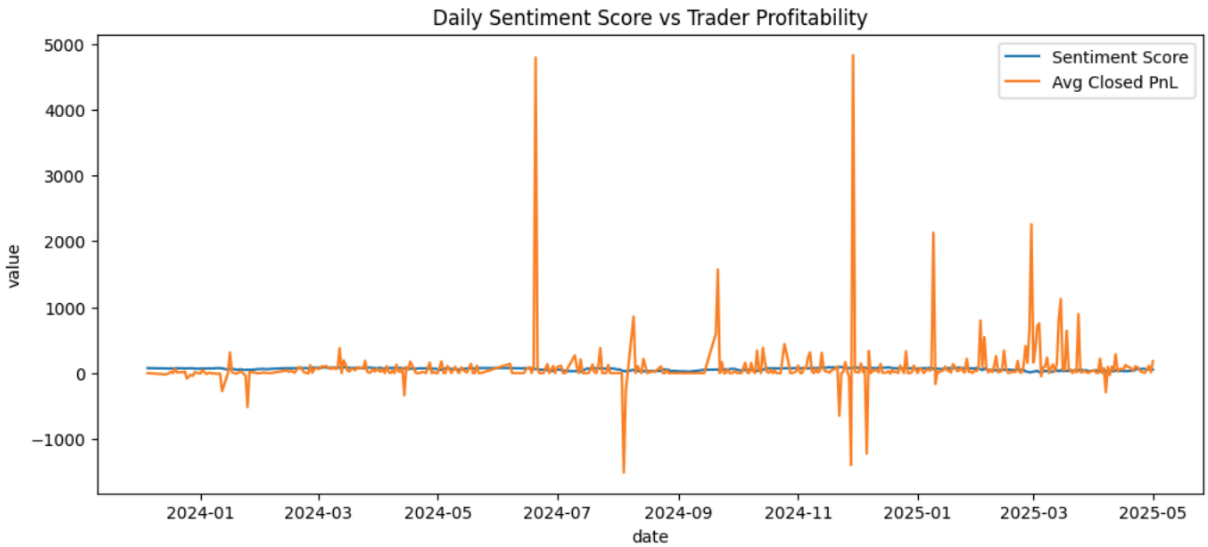


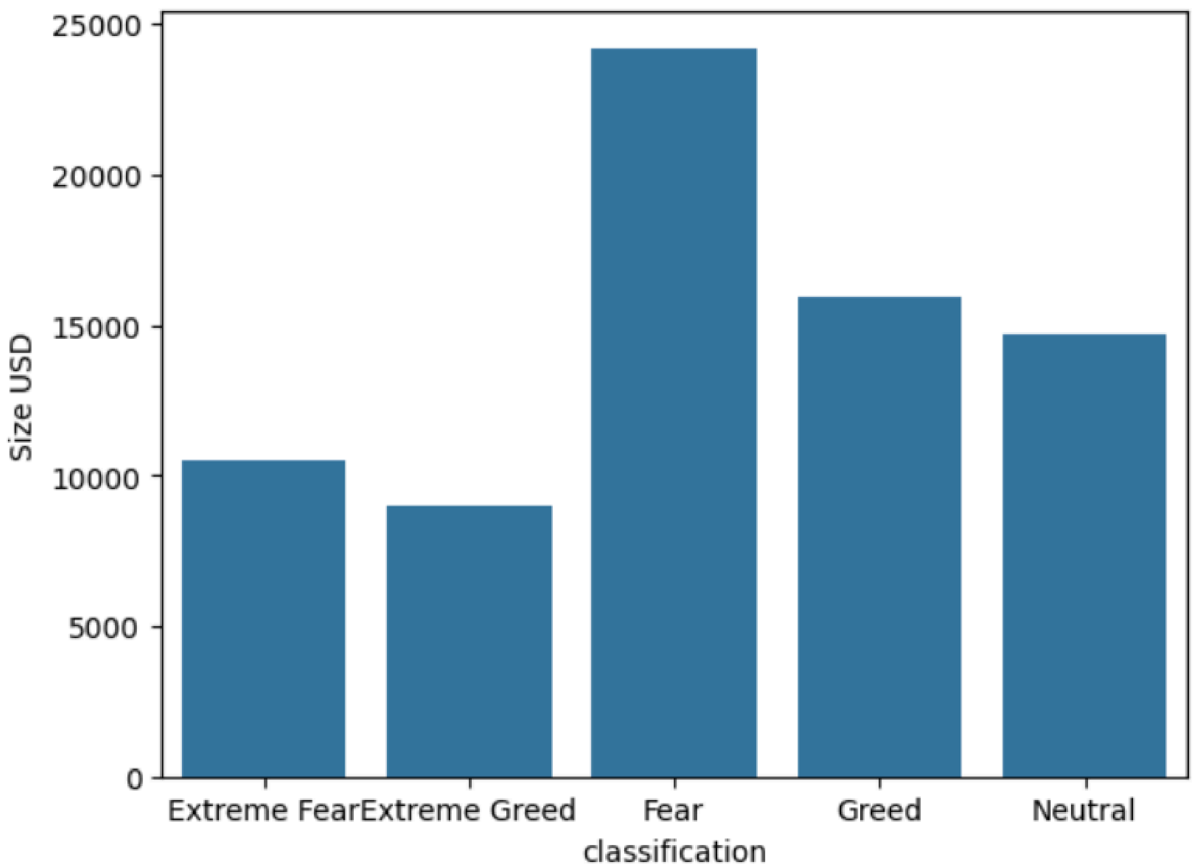

Next Day PnL by Previous Day's Sentiment
Closed PnL
500000
400000
300000
200000
100000
0
−100000
−200000
Extreme Greed
Greed
Neutral
Fear
Extreme Fear
prev_classification

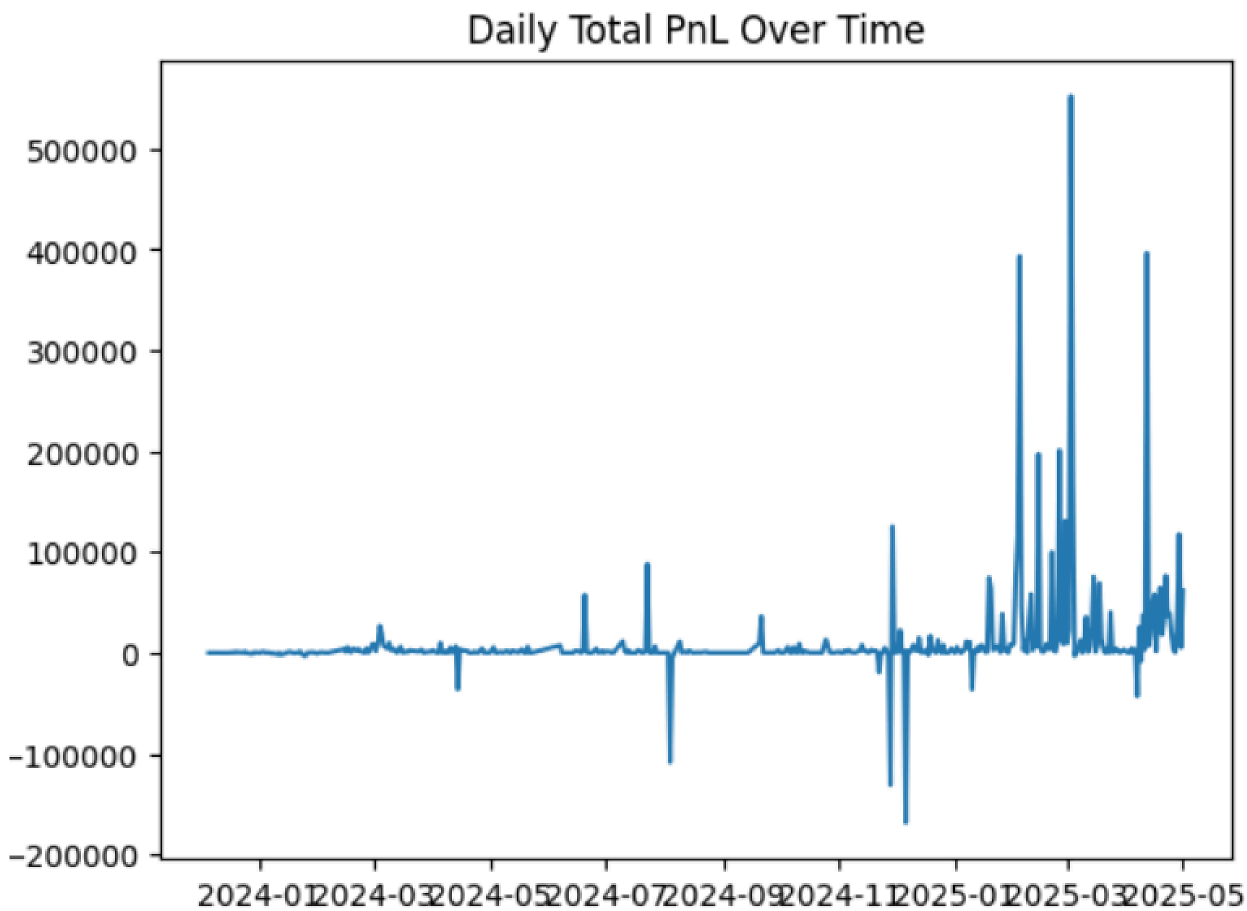

Sentiment Score (Prev Day) vs Next Day PnL
Closed PnL
500000
400000
300000
200000
100000
0
−100000
−200000
20
40
60
80
prev_value


Daily Profit Rate vs Market Sentiment Classification
Profit Rate (Profitable Trades / Total Trades)
1.0
0.8
0.6
0.4
0.2
0.0
Extreme Greed
Greed
Neutral
Fear
Extreme Fear
Market Sentiment Classification


Daily Buy Ratio vs Market Sentiment Classification
Buy Ratio (Buy Trades / Total Trades)
1.0
0.8
0.6
0.4
0.2
0.0
Extreme Greed
Greed
Neutral
Fear
Extreme Fear
Market Sentiment Classification


Daily Sentiment Score vs Trader Profitability
Sentiment Score
Avg Closed PnL
value
date
5000
4000
3000
2000
1000
0
−1000
2024-01
2024-03
2024-05
2024-07
2024-09
2024-11
2025-01
2025-03
2025-05


Size USD
classification
25000
20000
15000
10000
5000
0
Extreme Fear
Extreme Greed
Fear
Greed
Neutral



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4. Analysis & Insights

- **Profitability & Sentiment:** Traders tend to achieve the highest average profits on Extreme Fear days when market rebounds occur, despite immediate profits being lower during fearful periods.

- **Trader Behavior:** Buy ratios increase during Extreme Greed, showing higher market activity.

- **Lagging Effect:** The previous day's market sentiment has a measurable impact on trader performance, highlighting the importance of market timing.

```
[119] # PnL per day
daily_pnl = merged_df.groupby('date')['Closed PnL'].sum().reset_index()

sentiment_df = sentiment_df.sort_values('date')
daily_pnl = pd.merge(daily_pnl, sentiment_df, on='date', how='left')

daily_pnl['prev_classification'] = daily_pnl['classification'].shift(1)
daily_pnl['prev_value'] = daily_pnl['value'].shift(1)
avg_lagged = daily_pnl.groupby('prev_classification')['Closed PnL'].mean().sort_values(ascending=False)
print(avg_lagged)
```

```
prev_classification
Fear             28526.139637
Extreme Fear     21887.031989
Neutral          14337.958521
Greed             4041.608157
Extreme Greed     2734.938169
Name: Closed PnL, dtype: float64
```

The highest average profits are seen after Fear and Extreme Fear sentiment days, indicating that traders tend to earn more following fearful market conditions. In contrast, profits are much lower after Greed and Extreme Greed days.

- **Statistical Validation:** ANOVA-test showed significant differences in profits across sentiment classes (p-value << 0.05), confirming the impact is not due to random chance.

```
[122] from scipy.stats import f_oneway

# ANOVA test across sentiments
groups = [group['Closed PnL'].dropna() for name, group in merged_df.groupby('classification')]
f_stat, p_val = f_oneway(*groups)
print("F-statistic:", f_stat, "P-value:", p_val)
```

```
F-statistic: 8.31771203210547 P-value: 1.0574609942177175e-06
```

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5. Conclusion

Market sentiment is a valuable predictor of trader behavior and profitability in Bitcoin trading. Strategies that account for sentiment trends and lag effects may improve trading outcomes. Future work could incorporate predictive modeling or sentiment from other sources to further enhance insights.

📊 Summary of Findings: Market Sentiment vs Trader Performance

Profitability by Sentiment

Highest average profit occurs during Extreme Fear days (~$220), indicating some large profitable trades possibly from contrarian moves or rebounds.

Extreme Greed days show moderate average profit (~$55), lower than expected.

Fear days also show high average profits(

153),*whileGreedandNeutraldayshavecomparativelyloweraverageprofits*(

75–90).

Probability of Profitable Trades

The likelihood of a trade being profitable is highest on Extreme Greed days (~53%) and lowest on Extreme Fear days (43%).

Profitability rates on Fear, Greed, and Neutral days hover around 43–46%.

Lagging Effect of Sentiment

The previous day's sentiment strongly influences the next day's profits.

Notably, an Extreme Fear day preceding a trading day corresponds with the highest next-day profits (~$72,700), possibly reflecting market rebounds or strategic positioning by traders.

Previous Greed or Neutral days lead to significantly lower average next-day profits (~$13,000–14,000).

Correlation Between Sentiment Score and PnL

The correlation between the previous day's sentiment score and next day's profit is slightly negative (-0.11), suggesting that lower sentiment (more fear) might predict higher profits the following day.

Statistical Significance

A very low p-value (< 0.0001) from ANOVA confirms significant differences in average profits across sentiment categories. This indicates market sentiment has a meaningful and measurable impact on trader profitability, beyond random chance.

📌 Key Insight

Fearful market conditions, especially Extreme Fear, tend to suppress immediate profits but may create opportunities for higher gains the next day. This highlights potential for contrarian trading strategies that capitalize on sentiment-driven market rebounds.

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6. Appendix

- Full code and analysis are available in the attached notebook(s).

notebook_1.ipynb

- Additional charts and raw data files are stored in the GitHub repository.