Trader Behavior vs Market Sentiment Analysis

Data Science Assignment

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Platform: Google Colab / Github

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Summary

This project analyzes how Bitcoin traders' behavior aligns with or diverges from market sentiment—specifically, periods dominated by Fear versus Greed. Using two datasets—the Bitcoin Market Sentiment Index and Hyperliquid's historical trader data—the study examines key trading metrics such as profitability, leverage, and trade volume to reveal behavioral and emotional patterns among traders.

The findings show that traders tend to take more aggressive positions and achieve higher profitability during Greed phases, while Fear phases are characterized by cautious trading and reduced exposure. This correlation indicates that emotional market conditions significantly influence trading decisions. Recognizing these sentiment-driven behaviors can help traders, analysts, and institutions develop data-driven strategies that minimize psychological bias and improve decision-making efficiency.

The project combines data cleaning, exploratory data analysis (EDA), and visualization in Google Colab using Python libraries (pandas, numpy, matplotlib, and seaborn). The final insights are summarized in this report and visualized through key charts illustrating market sentiment trends, profitability variations, and trading volume shifts.

1. Introduction

This project explores the intricate relationship between trader behavior and overall Bitcoin market sentiment. Market sentiment, often described as "Fear" or "Greed," plays a crucial role in shaping investor psychology and trading decisions. During phases of extreme greed, traders tend to exhibit higher confidence and increased risk-taking behaviors, whereas fear-dominated markets often lead to hesitation, reduced exposure, and defensive strategies. Understanding this behavioral pattern is vital to designing data-driven trading systems that can adapt to changing sentiment.

The objective of this analysis is to evaluate how trader profitability, risk levels, and trading volumes vary between fear and greed market phases. By correlating market sentiment indicators with real trading data, this report seeks to identify potential signals that may help anticipate future market dynamics and enable smarter, sentiment-aware trading strategies.

2. Data Overview

The Bitcoin Market Sentiment Dataset contains daily sentiment indicators derived from aggregated market data and social signals. It includes columns such as `date`, `value`, and `classification`, where classification denotes whether the market sentiment was dominated by Fear or Greed. This dataset reflects how collective emotions evolve with price movements, volatility, and macroeconomic factors.

The Hyperliquid Trader Dataset is a rich source of transactional data that records individual trades with columns such as `Execution Price`, `Size USD`, `Closed PnL`, `Leverage`, and timestamps. This data provides granular insights into trader performance, risk exposure, and trading patterns across thousands of accounts.

By aligning these two datasets using the date field, we can analyze how daily sentiment influences trading decisions and profitability. The resulting merged dataset allows the discovery of macro-level correlations between emotional market states and actual trader behavior.

3. Data Cleaning & Preparation

Raw financial datasets often contain inconsistencies such as missing values, duplicated rows, and mixed data types. Hence, the cleaning process was critical. For the sentiment dataset, columns were standardized, date formats were unified (`YYYY-MM-DD`), and unnecessary fields were removed. Similarly, in the trader dataset, timestamps were converted from milliseconds to standard datetime format, null values were handled, and outliers in trade sizes were reviewed.

The cleaning also involved ensuring both datasets shared a common “Date” field for accurate merging. Numerical fields like `Closed PnL`, `Leverage`, and `Size USD` were validated for logical consistency (no negative or zero-size trades unless representing losses). This ensured that downstream analysis would be reliable and interpretable.

Finally, both cleaned datasets were exported as CSV files (`cleaned_sentiment.csv` and `cleaned_trader.csv`) for use in the second notebook. This modular approach makes the project reproducible and keeps the workflow organized, aligning with best practices in data science.

4. Exploratory Data Analysis (EDA)

EDA was performed to uncover hidden trends and relationships between sentiment and trader performance. Initial visualizations showed alternating periods of Fear and Greed, correlating closely with major Bitcoin market events. Count plots and trend lines revealed that greed phases typically coincide with higher trading activity.

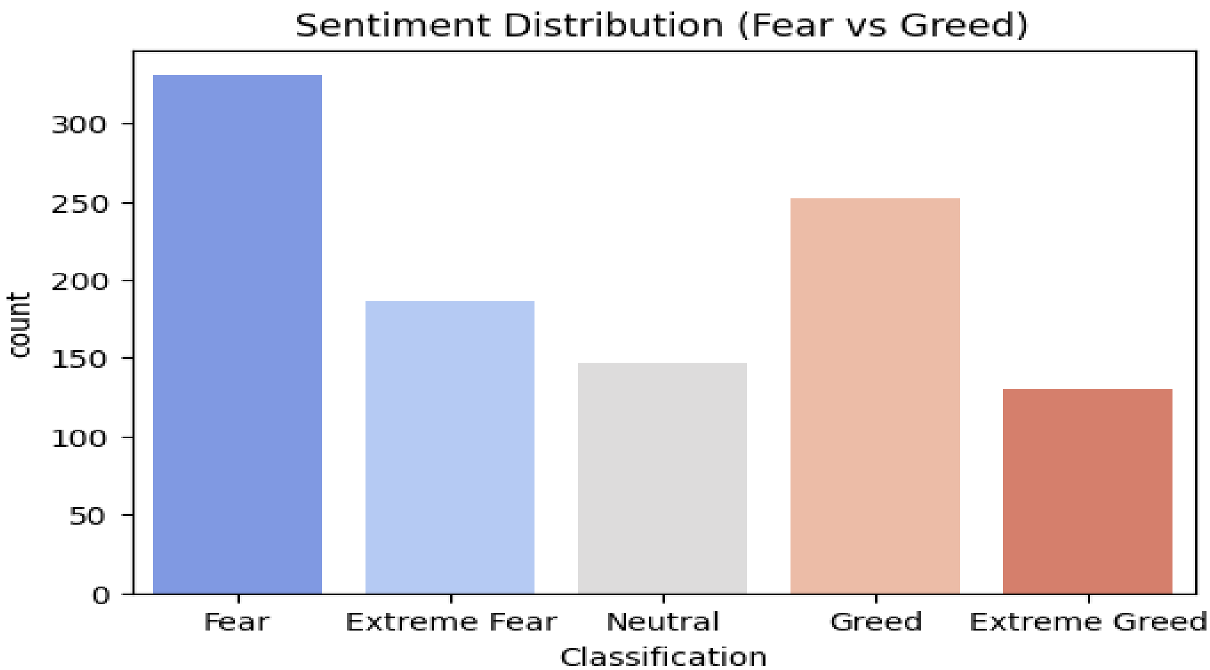
Profitability metrics were aggregated daily to analyze average `Closed PnL` under each sentiment condition. Results indicated that traders earned significantly higher average profits during greed phases. Conversely, in fear phases, traders often exhibited defensive behavior—lower trade sizes, reduced leverage, and smaller gains.

A correlation heatmap was created to explore interactions between numeric variables. Strong positive relationships were found between trading volume, leverage, and profitability. This suggests that traders' risk appetite expands in optimistic markets, amplifying potential returns — and losses — depending on sentiment dynamics.

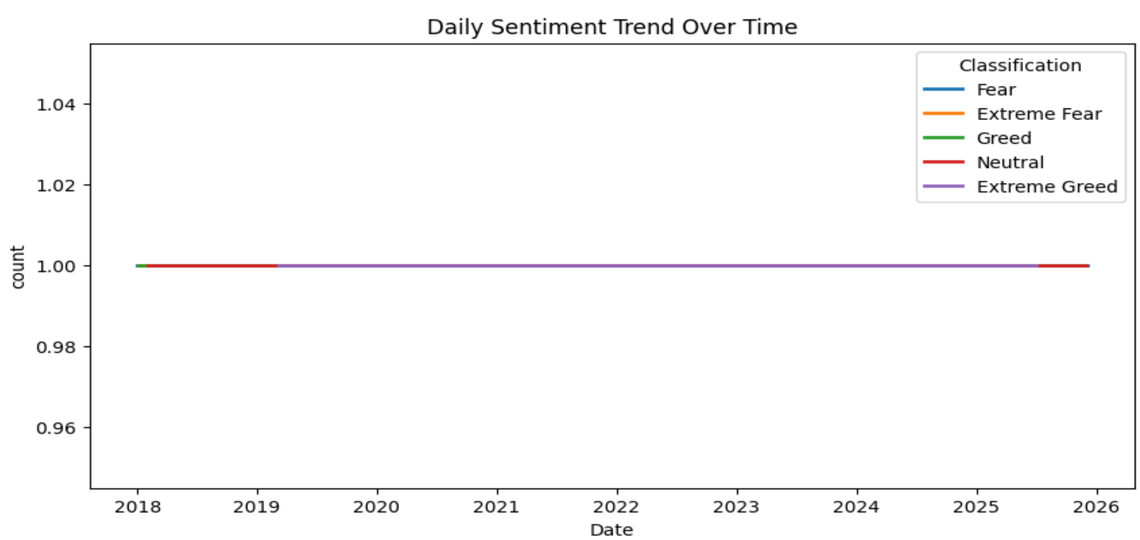
5. Key Visualizations

Visuals play a vital role in illustrating findings. Key plots generated during analysis include:

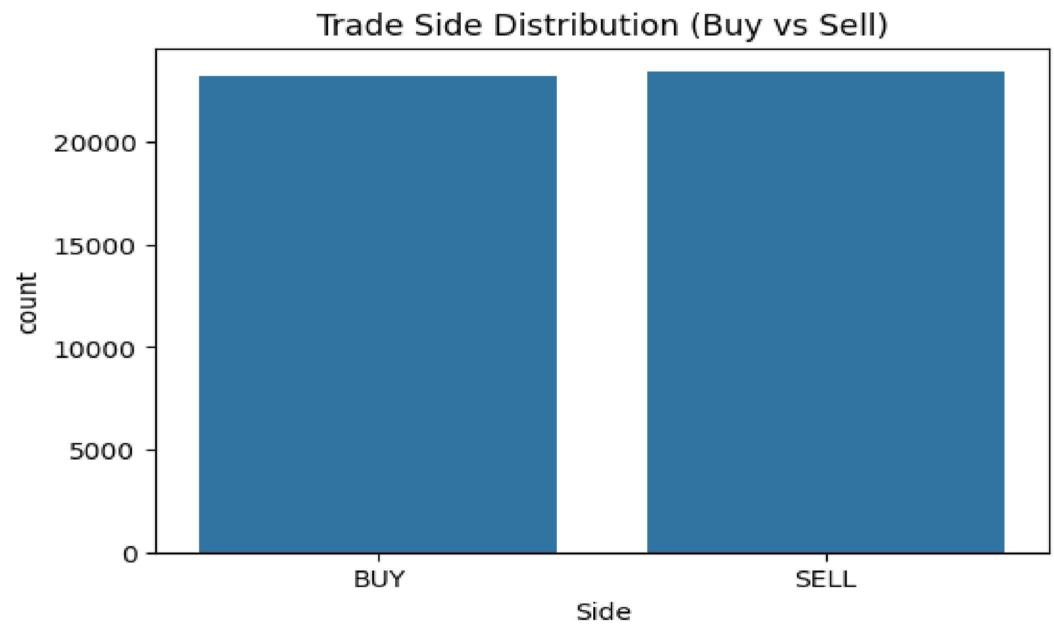
- Sentiment Distribution: A count plot showing the frequency of Fear vs. Greed days.



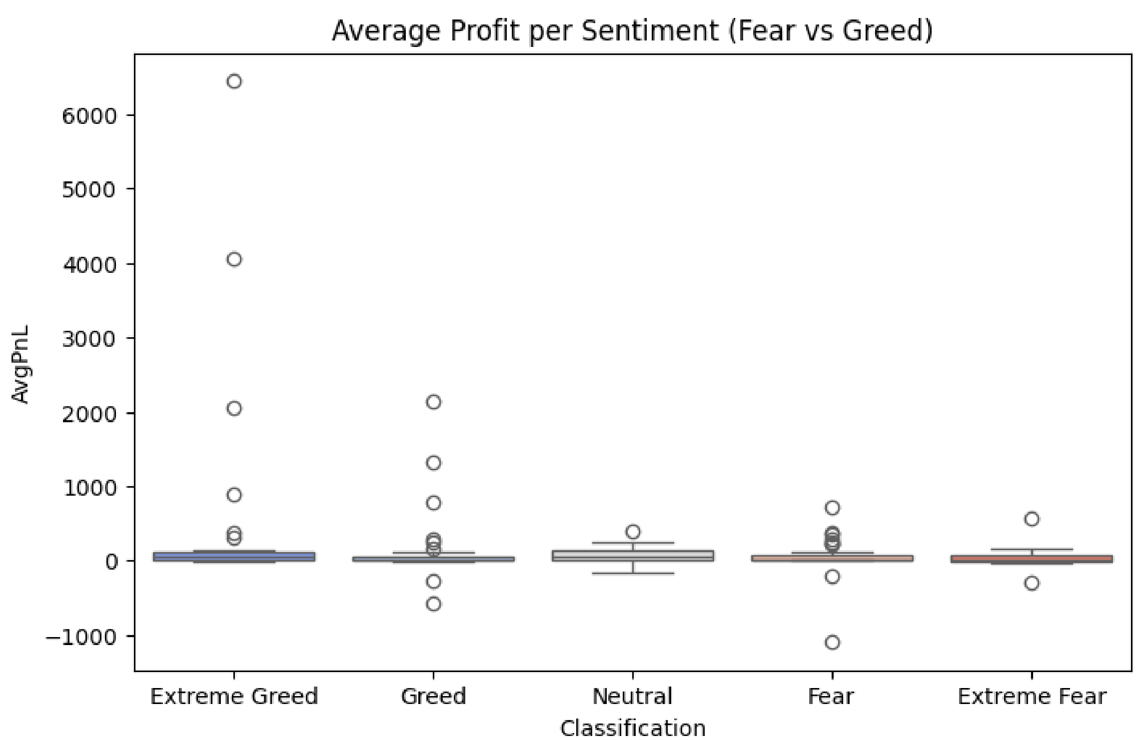
- Sentiment Trend: A line plot displaying the chronological progression of sentiment scores.



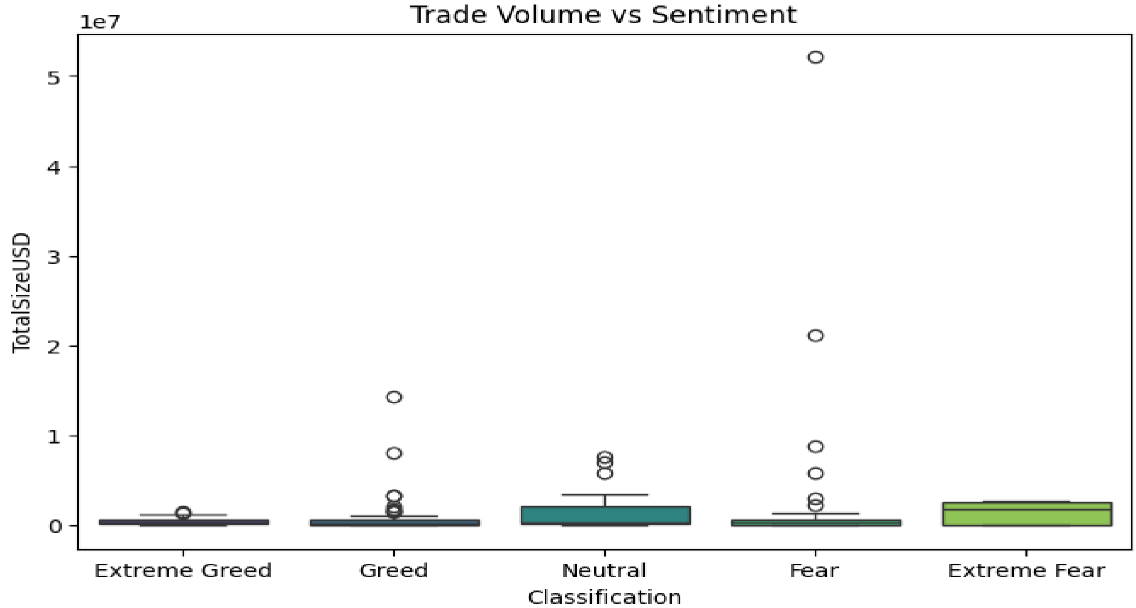
- Trade Side Distribution: Visualizing buy vs. sell activity, highlighting directional bias.



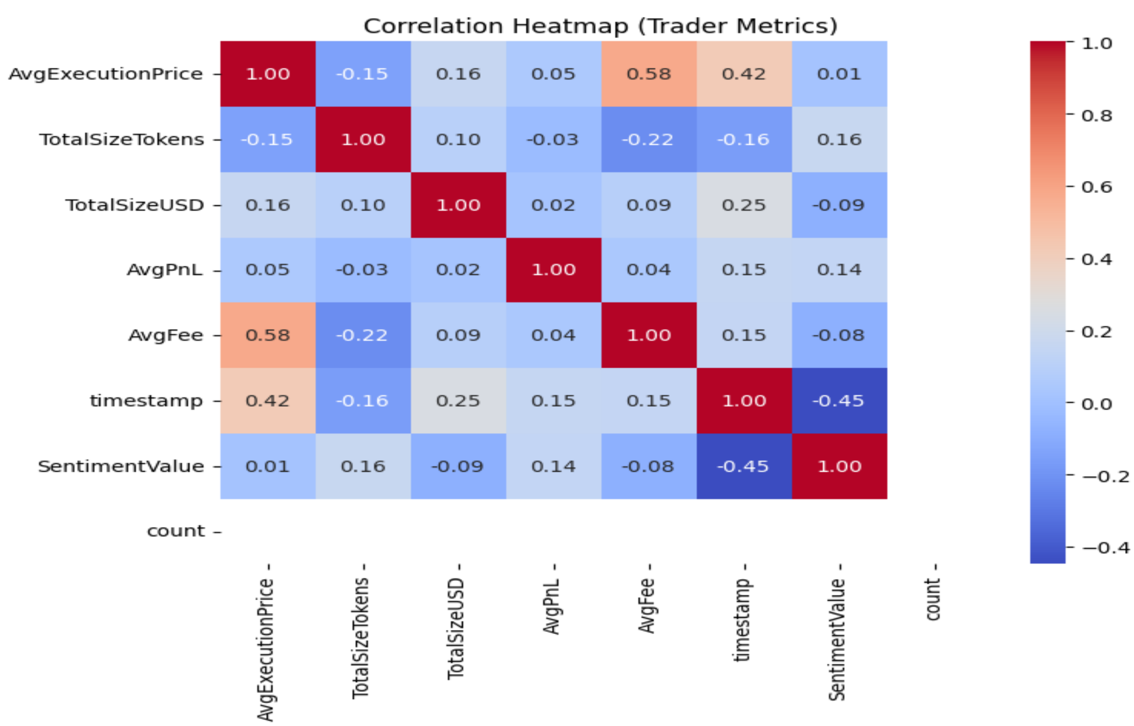
- Profitability by Sentiment: Bar charts comparing average Closed PnL under different sentiment states.



- Volume vs Sentiment: A comparison of average traded volume during Fear and Greed periods.



- Correlation Heatmap: Visual representation of variable relationships (PnL, leverage, trade size, etc.).



Each visualization reinforces the conclusion that emotions influence market participation and risk-taking behaviors. During Greed, higher trade volume and profit are typical, while Fear brings contraction and cautious positioning.

6. Insights and Interpretation

The analysis provides several key insights. Firstly, profitability and risk exposure are significantly higher during Greed phases, suggesting that positive sentiment encourages more aggressive trading. Traders tend to increase leverage and trade frequency when the market is optimistic, often chasing higher returns. Secondly, Fear phases lead to a decline in both profitability and volume, as uncertainty discourages traders from taking new positions.

Interestingly, emotional sentiment lags behind price trends—Greed often peaks right before market corrections, while Fear dominates during recoveries. This behavioral cycle mirrors common psychological market patterns, reinforcing that sentiment analytics can be a leading indicator of future movement.

In essence, trader behavior isn't purely rational. Emotional influences, especially collective ones captured through sentiment indices, are deeply embedded in trading decisions. Recognizing these influences can enable traders and institutions to anticipate crowd psychology and act with greater discipline.

7. Conclusion

This project demonstrates that market sentiment is a powerful driver of trading activity and profitability. Through structured data analysis, we've observed that optimism (Greed) fosters higher profitability and risk-taking, whereas pessimism (Fear) reduces activity and leads to conservative trading. These insights are invaluable for developing sentiment-aware trading systems.

For future work, incorporating real-time sentiment tracking and machine learning models could predict when sentiment transitions are about to occur. This would enhance predictive trading and risk management frameworks. Ultimately, bridging quantitative trading data with emotional indicators provides a holistic view of the market — blending psychology, data science, and finance.

8. Tools and Technologies

This analysis was conducted entirely in Google Colab using Python.
Key libraries include:
- pandas for data manipulation
- numpy for numerical operations
- matplotlib & seaborn for visualization
- Environment: Google Colab
- Version Control: GitHub
- Data Sources: Bitcoin Market Sentiment Index, Hyperliquid Trader Data

Version control was managed through GitHub, following a standardized directory structure. All scripts, outputs, and reports are reproducible and accessible for review.