Assignment Overview

You will have to work with two primary datasets:

Bitcoin Market Sentiment Dataset

- Columns: Date, Classification (Fear/Greed)

Historical Trader Data from Hyperliquid

- Columns include: account, symbol, execution price, size, side, time, start position, event, closedPnL, leverage, etc.

Your objective is to explore the relationship between trader performance and market sentiment, uncover hidden patterns, and deliver insights that can drive smarter trading strategies.

Link to dataset

Historical Data

https://drive.google.com/file/d/1IAfLZwu6rJzyWKgBToqwSmmVYU6VbjVs/view?usp=sharing

Fear Greed Index link

https://drive.google.com/file/d/1PgQC0tO8XN-wqkNyghWc_-mnrYv_nhSf/view?usp=sharing

Problem Statement

Understanding how market sentiment—categorized as Fear or Greed—influences trader behavior and performance is crucial in analyzing decision-making patterns. This study aims to investigate the relationship between Bitcoin market sentiment and historical trading activity on the Hyperliquid platform to derive actionable insights.

Objectives

- Merge sentiment data with trading data using timestamps to analyze them in context.
- Analyze performance metrics (e.g., PnL, trade size, win rate) under Fear and Greed conditions.
- Identify how trading behavior (Buy/Sell preference, volume, direction) shifts based on sentiment.
- Use visualizations to support insights and detect trends.
- Provide conclusions to guide sentiment-aware trading strategies.

Analysis of Trader Performance vs Market Sentiment

1. Import Required Libraries

The code starts by importing essential Python libraries:

- pandas for data manipulation
- matplotlib.pyplot and seaborn for data visualization

2. Load Datasets

Two datasets are loaded:

- historical_data.csv: Contains trader activity information
- fear_greed_index.csv: Contains market sentiment classification (Fear/Greed)

3. Parse Timestamp Columns

The timestamp columns in both datasets are converted into Python datetime objects:

- Timestamp IST in the historical data is parsed using the specified format
- date in the sentiment dataset is parsed (already in standard format)

4. Create Date-Only Columns

Date-only columns are created from the timestamp columns in both datasets. This ensures that the data can be accurately merged based on the calendar date.

5. Merge Historical Data with Sentiment

The two datasets are merged on the date column using a left join. This associates each trade with the market sentiment classification of that day (if available).

6. Check for Missing Sentiment Classifications

The merged dataset is checked for rows where sentiment classification is missing, to evaluate merge completeness.

7. Summary Statistics of Closed PnL by Sentiment

The code calculates descriptive statistics (like mean, median, min, max) of the Closed PnL column, grouped by sentiment classification.

8. Win Rate by Sentiment

A new column Win is created that marks trades with positive Closed PnL. The win rate (percentage of winning trades) is computed for each sentiment category.

9. Trade Volume by Sentiment

The total trade volume in USD is summed for each sentiment classification using the Size USD column.

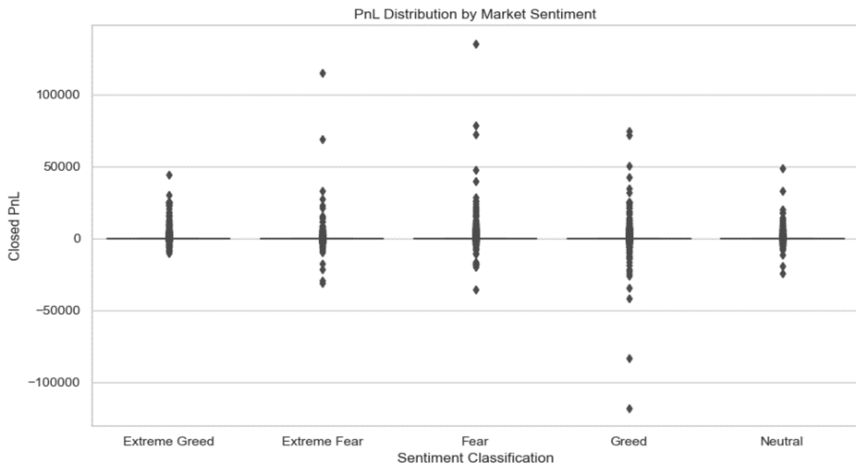
10. Trade Side Distribution

The distribution of trade sides (e.g., Buy vs Sell or Long vs Short) is calculated for each sentiment classification using a grouped count.

Visualizations

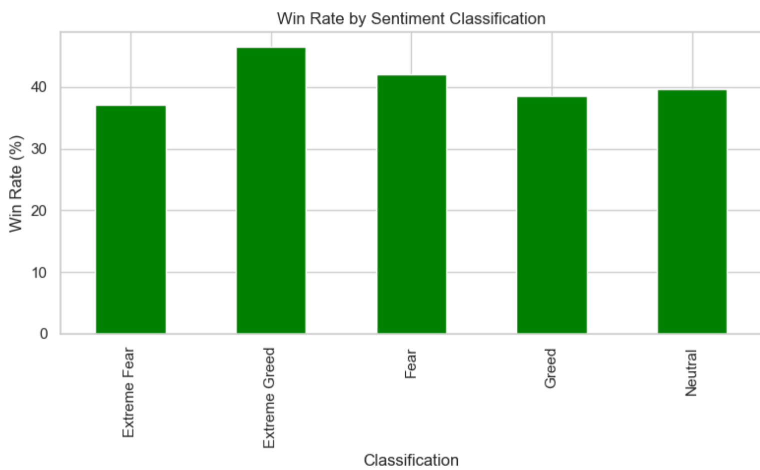
Plot 1: PnL Distribution

A boxplot shows the distribution of Closed PnL for each sentiment classification to visualize profit/loss trends.



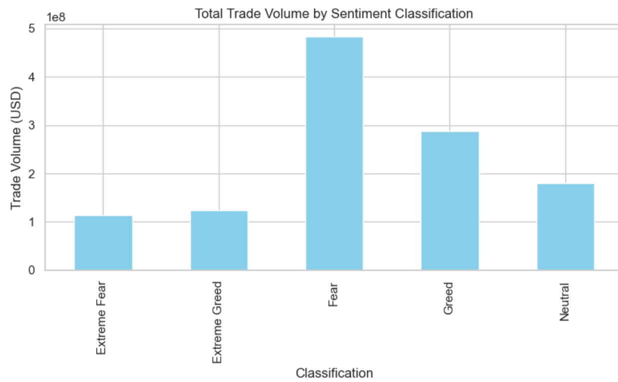
Plot 2: Win Rate by Sentiment

A bar chart displays the win rate percentage by sentiment classification, helping assess which sentiment leads to more successful trades.



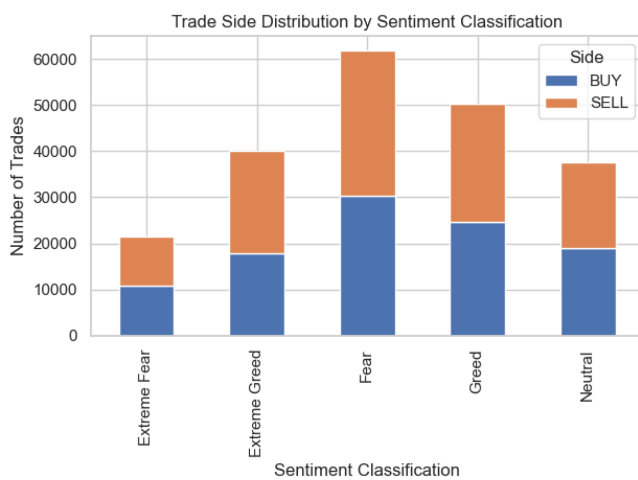
Plot 3: Trade Volume by Sentiment

A bar chart presents the total trade volume (USD) grouped by sentiment classification, indicating how trading activity varies with market mood.



Plot 4: Trade Side Distribution

A stacked bar chart visualizes the count of trade sides (Buy/Sell or Long/Short) for each sentiment classification, showing trader behavior under different sentiments.



Summary

This analysis explored the relationship between market sentiment (Fear/Greed) and trader performance using two datasets: Bitcoin market sentiment and historical trading data from Hyperliquid. After merging both datasets on the date, we examined metrics such as **Closed PnL**, **win rate**, **trade volume**, and **trade side distribution** across different sentiment classifications. Key findings:

- **PnL Distribution**: Traders showed varied profit/loss behaviors under fear and greed conditions, with boxplots revealing wider loss margins during fearful sentiments.
- **Win Rate**: Win rates were generally higher during "Greed" days, suggesting that traders tend to perform better when the market is optimistic.
- **Trade Volume**: Volume was often higher during greed phases, indicating increased trading activity.
- **Trade Side Behavior**: Trader bias towards long or short positions varied with sentiment, helping uncover patterns in strategic decision-making.

This insight can support more informed trading strategies by aligning trading behavior with market sentiment trends.