Trader Behavior vs Market Sentiment (Fear–Greed Analysis)

Candidate: Sarthak Pant

Dataset: Hyperliquid Trader Data & Bitcoin Fear–Greed Index

1. Introduction

Financial markets are heavily influenced by trader psychology and market sentiment.
This project analyzes **how trader behavior (profitability, volume, activity)** varies across different **market sentiment regimes (Fear vs Greed)** using real historical trading data and the Bitcoin Fear–Greed Index.

The goal is to identify **behavioral patterns** that can support **risk-aware trading strategies** in Web3 markets.

2. Datasets Used

2.1 Historical Trader Data (Hyperliquid)

Contains trade-level information such as:

- Execution price
- Trade size (tokens & USD)
- Side (Buy / Sell)
- Closed PnL
- Fees
- Timestamps

Each trade represents a completed position.

2.2 Bitcoin Fear–Greed Index

Daily market sentiment classified into:

- **Fear**
- **Greed**

This dataset reflects overall market psychology.

3. Data Cleaning & Preprocessing

Key preprocessing steps included:

- Normalizing column names
- Converting timestamps to datetime format
- Handling missing numeric values
- Filtering invalid trades (zero or negative size)
- Aggregating trade-level data to **daily-level metrics**

This ensured consistency and prevented data leakage during analysis.

4. Methodology

4.1 Directional Analysis

Trades were grouped by **Buy vs Sell** to evaluate directional profitability.

Metrics:

- Total PnL
- Number of trades
- Average PnL per trade

4.2 Daily Aggregation

Trade-level data was aggregated by date to compute:

- Daily PnL
- Daily trading volume
- Number of trades per day
- Average transaction fee

This step enabled time-based and sentiment-based analysis.

4.3 Risk Metrics

To evaluate strategy stability:

- **Cumulative PnL (Equity Curve)**
- **Maximum Drawdown**
- **Sharpe Ratio (risk-adjusted return)**

4.4 Sentiment Alignment

Daily trader metrics were merged with the Fear–Greed dataset on the date field.
This allowed direct comparison of trader behavior under different sentiment regimes.

5. Key Results & Insights

5.1 Directional Performance

- Buy-side and sell-side trades exhibited **asymmetric profitability**
- Average PnL per trade varied significantly across directions

5.2 Performance Across Sentiment Regimes

Metric	Fear	Greed
Avg Daily PnL	Lower	Higher
Win Rate	Lower	Higher
Trading Volume	Elevated	Moderately High
Drawdowns	Deeper	Shallower

Key Observation:
Traders tend to be **more profitable and consistent during Greed**, while **Fear periods show higher volatility and drawdowns**, indicating emotional or reactive trading behavior.

5.3 Risk Behavior

- Maximum drawdowns were **significantly larger during Fear**
- Risk-adjusted returns (Sharpe Ratio) were superior during Greed

6. Actionable Insights

- **Reduce exposure during Fear periods** to control drawdowns
- **Increase position sizing selectively during Greed** when win rates improve
- Sentiment-aware position sizing can materially improve risk-adjusted performance

7. Conclusion

This analysis demonstrates a clear relationship between **market sentiment and trader performance**.
Incorporating sentiment signals into trading strategies can lead to:

- Better capital preservation
- Improved consistency
- Smarter risk allocation

The framework developed here can be extended to:

- Asset-level analysis
- Strategy backtesting
- Automated sentiment-based risk controls

8. Tools & Technologies

- Python (Pandas, NumPy, Matplotlib)
- Google Colab
- GitHub
- CSV-based data pipelines