Title

Trader Performance vs Market Sentiment: Insights from Hyperliquid Trading Data

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1. Introduction

Financial markets are heavily influenced by trader psychology, particularly during periods of extreme fear or greed. In crypto markets, where volatility is amplified, understanding how trader behavior aligns with market sentiment can provide a competitive edge.

This project analyzes the relationship between **Bitcoin market sentiment (Fear & Greed Index)** and **actual trader behavior and performance** using historical trade-level data from Hyperliquid. The goal is to uncover actionable insights that can guide smarter trading strategies in Web3 markets.

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2. Datasets Overview

2.1 Bitcoin Market Sentiment Dataset

- Date
- Sentiment Classification (Extreme Fear, Fear, Neutral, Greed, Extreme Greed)
- Sentiment Index Value (0–100)

2.2 Historical Trader Data (Hyperliquid)

- Trade-level data including:
    - Account, Coin, Side
    - Execution Price, Size (USD)
    - Closed PnL
    - Timestamps and trade identifiers

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3. Methodology

3.1 Data Cleaning & Preprocessing

- Converted timestamps to daily granularity
- Removed missing or invalid PnL values
- Aggregated trades at **daily level** to align with sentiment data
- Standardized sentiment into ordinal categories

3.2 Feature Engineering

Created daily metrics:

- **Total Daily PnL**
- **Average PnL per Trade**
- **Trade Count**
- **Total Trading Volume**
- **Sentiment Code (ordinal encoding)**

3.3 Analytical Techniques

- Time-series analysis
- Correlation analysis
- Sentiment-wise distribution analysis
- ANOVA testing
- OLS regression
- Trader behavior clustering (K-Means)

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4. Exploratory Data Analysis & Findings

4.1 PnL Behavior Across Market Sentiment

- Greed phases show **stable but moderate profitability**
- Fear and Extreme Fear periods exhibit **high volatility**
- Largest positive and negative PnL spikes occur during fear-driven regimes

Insight:
Fear introduces inefficiencies that skilled traders can exploit, but with increased downside risk.

4.2 Correlation Analysis

Key observations:

- Total PnL correlates strongly with:
  - **Trade Count (0.48)**
  - **Total Volume (0.56)**
- Sentiment shows **weak negative correlation** with profitability

Interpretation:
Profitability depends more on **participation and liquidity** than sentiment alone.

4.3 Sentiment-wise PnL Distribution

- Median PnL increases during Fear and Extreme Fear
- Extreme Fear shows the widest variance (highest risk–reward)

Implication:
Extreme Fear favors **selective, conviction-based trading**, not over-leveraged strategies.

4.4 Trader Behavior Clustering

Three trader archetypes emerged:

1. **Conservative Traders**
    - Low trade frequency
    - Stable returns
    - Active mainly during Greed
2. **Opportunistic Traders**
    - Balanced risk
    - Consistent profitability
    - Sentiment-agnostic
3. **Aggressive Traders**
    - High trade count
    - High volatility PnL
    - Most active during Fear regimes

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5. Statistical Analysis

5.1 ANOVA

- p-value = 0.084
- Sentiment alone is **not statistically significant**

5.2 Regression Analysis

Significant predictor:

- **Total Trading Volume (p < 0.001)**

Non-significant:

- Sentiment code

- Trade count

Conclusion:
Sentiment acts as a **contextual signal**, not a direct profitability driver.

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6. Strategic Takeaways for Trading Teams

What Works

- Capital-efficient strategies during high volatility
- Volume-based participation
- Opportunistic trades during Fear regimes

What Fails

- Blind sentiment-following
- Excessive leverage during Extreme Fear
- High-frequency trading without liquidity filters

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7. Conclusion

This analysis demonstrates that while market sentiment influences volatility and trader behavior, **liquidity and participation intensity** are the primary drivers of profitability. Sentiment should be used as a **risk-context indicator**, combined with volume and execution-aware strategies to improve trading outcomes in Web3 markets.