# Trader Behavior Analysis Under Market Sentiment Regimes

***Understanding the Impact of Fear & Greed on Hyperliquid Trader Performance***

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**Google Colab notebook link**:
https://colab.research.google.com/drive/1SMUku6FlKDjKy03gkLAYUd62hFRCnh1M?usp=sharing

## 1. Introduction

Financial markets are not driven solely by fundamentals or technical indicators; trader psychology plays a crucial role in shaping price movements and execution outcomes. In cryptocurrency markets, where volatility is high and retail participation is significant, **market sentiment** often amplifies behavioral biases such as fear, overconfidence, and herd behavior.

This project aims to analyze how **Bitcoin market sentiment**, measured using the **Fear & Greed Index**, influences **trader behavior and performance** on the Hyperliquid platform. Specifically, the analysis explores how profitability, trade sizing, win rates, and risk exposure vary across different sentiment regimes. The ultimate objective is to uncover **hidden behavioral patterns** that can inform **smarter, sentiment-aware trading strategies**.

## 2. Datasets Overview

### 2.1 Bitcoin Fear & Greed Index

This dataset provides a daily snapshot of overall market sentiment. It categorizes market conditions into the following regimes:

- Extreme Fear
- Fear
- Neutral
- Greed
- Extreme Greed

Each day is also associated with a numerical sentiment score, representing the intensity of the sentiment.

**Purpose in analysis:**
The Fear & Greed Index serves as a proxy for collective market psychology and is used to segment trading behavior under different emotional market states.

### 2.2 Hyperliquid Historical Trader Data

This dataset contains **trade-level execution data** from multiple traders, including:

- Account identifiers
- Execution prices
- Trade size (USD)
- Trade direction (buy/sell)
- Timestamps
- Closed profit and loss (PnL)

**Purpose in analysis:**
This data enables a granular evaluation of how individual traders perform and manage risk under different market sentiment conditions.

## 3. Data Preparation & Challenges

### 3.1 Timestamp Misalignment Issue

A key challenge identified during data integration was a **timezone mismatch**:

- Hyperliquid trade timestamps were recorded in **IST (India Standard Time)**
- Fear & Greed Index dates were recorded in **UTC**

An initial merge attempt resulted in no matching records, which highlighted a real-world data engineering issue commonly encountered in multi-source financial datasets.

### 3.2 Resolution

To resolve this:

- Trade timestamps were converted from **IST to UTC**

- A UTC-based trade date was extracted
- The datasets were then merged using aligned UTC dates

Only trades with valid sentiment labels were retained for analysis. This ensured temporal consistency and analytical accuracy.

## 4. Feature Engineering

To translate raw data into meaningful insights, several features and metrics were created:

**Trade-Level Features**

- Binary profitability indicator (Closed PnL > 0)
- Trade size in USD

**Trader-Level Aggregations**

Metrics were calculated per trader and sentiment regime, including:

- Total and average PnL
- Win rate
- Total number of trades
- Average trade size
- Total traded volume

These features allow both **micro-level (trade)** and **macro-level (trader behavior)** analysis.

## 5. Exploratory Data Analysis

### 5.1 Profitability Across Sentiment Regimes

Analysis of average PnL per trade revealed clear sentiment-dependent behavior:

- **Extreme Greed** exhibited the highest average PnL and win rate
- **Fear and Extreme Fear** showed lower win rates but meaningful profitability

**Insight:**
High profitability does not always coincide with high accuracy. In fear-driven markets, traders

often benefit from **asymmetric payoffs**, where a smaller number of winning trades compensate for frequent losses.

### 5.2 Distribution of Trade Outcomes

The distribution of closed PnL was **highly right-skewed**:

- Most trades resulted in small gains, losses, or breakeven outcomes
- A small number of trades generated very large profits

**Interpretation:**
Overall trader performance is driven by **capturing a few high-impact opportunities**, rather than consistently winning small trades.

### 5.3 Risk Behavior and Trade Sizing

Trade size analysis across sentiment regimes showed that:

- Largest average trade sizes occurred during **Extreme Fear**
- Smallest trade sizes occurred during **Extreme Greed**

**Behavioral explanation:**
During fear, traders tend to “buy the dip” aggressively, increasing exposure. During greed, traders appear more cautious, potentially due to profit-taking or risk awareness.

### 5.4 Trade Size vs Profitability

Scatter analysis between trade size and PnL showed:

- No strong linear relationship
- Many large trades resulted in losses

**Conclusion:**
Increasing position size does not guarantee profitability. Execution quality and timing are more critical than sheer exposure.

**5.5 Cumulative PnL Over Time**

Cumulative PnL analysis revealed:

- Long flat periods with minimal gains
- Sudden upward jumps during specific market windows

**Insight:**
Profits tend to be generated during **short, sentiment-driven opportunities**, reinforcing the importance of timing and market context.

## 6. Trader Segmentation

Based on observed patterns, three broad trader archetypes emerged:

**1. Contrarian Traders**

- Perform relatively well during fear regimes
- Take larger positions
- Lower win rates but higher payoff per winning trade

**2. Momentum Traders**

- Perform best during greed and extreme greed
- Use smaller, more controlled trade sizes
- Higher win rates and smoother equity curves

**3. Overconfident Traders**

- Consistently large trade sizes
- Poor sentiment adaptation
- Flat or negative long-term PnL

## 7. Strategy Implications

The findings suggest several actionable insights:

- Market sentiment should be used as a **risk-management filter**

- Fear regimes may favor **selective contrarian strategies**
- Greed regimes are better suited for **momentum-based strategies**
- Consistent profitability is associated with:
    - Moderate position sizing
    - Frequent participation
    - Adaptation to sentiment changes

## 8. Limitations

- Sentiment data is available only at a daily frequency
- Not all trades could be aligned with sentiment data
- Leverage-specific analysis was limited due to data granularity

Despite these limitations, the dataset was sufficient to uncover meaningful behavioral patterns.

## 9. Conclusion

This analysis demonstrates that **market sentiment has a significant and measurable impact on trader behavior and performance**. Traders who adapt their strategies to sentiment regimes—by adjusting risk exposure, timing, and execution—tend to outperform those who do not.

Incorporating sentiment awareness into trading systems can enhance decision-making, improve risk control, and increase long-term profitability. These insights are particularly valuable in high-volatility environments such as cryptocurrency markets.