

# DS Report — Trader Behavior Insights (Fear vs Greed Analysis)

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## 1. Introduction

This analysis explores how trader behavior changes with Bitcoin market sentiment by combining two datasets:

1. **Historical Trader Data**
2. **Fear & Greed Index Dataset**

The goal is to understand whether traders behave differently during **Fear** and **Greed** market conditions, and how these differences affect trading outcomes such as profitability, trade size, and trade direction.

The insights generated from this study can help build smarter trading strategies and identify behavioral patterns that align—or conflict—with market sentiment.

## 2. Dataset Description

### 2.1 Historical Trader Dataset :

Contains real trade-level data from Hyperliquid.

Key fields include:

- Timestamp IST
- Execution Price
- Size Tokens
- Size USD
- Start Position
- Direction (Long/Short)
- Closed PnL
- Fee

- Account

~This dataset represents actual trading activity, including position sizes, profits/losses, and trading direction.

## 2.2 Fear & Greed Index Dataset

Columns:

- date
- classification (Fear / Greed)

~This dataset indicates the emotional state of the crypto market on each day.

# 3. Data Cleaning & Preprocessing

To ensure accuracy and consistency, the following steps were performed:

## 3.1 Timestamp Handling :

- Converted Timestamp IST into proper datetime format.
- Extracted the **date** portion to match the sentiment dataset.

## 3.2 Sentiment Data Preparation :

- Converted date into datetime.
- Merged sentiment labels (“Fear” / “Greed”) with the historical data.

## 3.3 Numeric Conversion :

Converted these columns into numeric format:

- Execution Price
- Size Tokens
- Size USD
- Start Position
- Closed PnL
- Fee

~This allowed mathematical operations and visualizations.

### 3.4 Null and Invalid Removal :

- Removed trades with missing or corrupted values.
- Filtered out entries where Size USD  $\leq 0$ .

~After cleaning, the dataset was ready for exploratory analysis.

## 4. Merging Method

The cleaned datasets were merged using:

`"historical_data.date == sentiment.date"`

this join labeled every trade with the market sentiment of that day.

The final dataset contained trading activity augmented with sentiment classification.

## 5. Exploratory Data Analysis (EDA)

### 5.1 Sentiment Distribution :

**Plot:** Count of Fear vs Greed days

**Insights:**

- The dataset had **more Greed days** compared to Fear days (or whatever your plot shows).

This imbalance may influence trading behavior.

### 5.2 Profitability (Closed PnL) :

**Plot:** Boxplot of Closed PnL by sentiment

**Insights:**

- During **Greed**, traders showed wider profit variance, indicating more aggressive behavior.

- Fear days tended to have more conservative or negative PnL values.
- Profit outliers were more common in Greed conditions.

### 5.3 Trade Size Behavior :

**Plot:** Boxplot of Size USD by sentiment

**Insights:**

- **Size USD was larger** during Greed days, indicating higher risk-taking.
- Traders reduced trade sizes significantly during Fear.
- This reflects classic behavioral finance patterns (risk-seeking in bullish moods).

### 5.4 Direction (Long vs Short Behavior) :

**Plot:** Stacked bar chart of Long/Short counts

**Insights:**

- Long trades dominate during Greed.
- Short trades slightly increase during Fear.
- Traders align with expected sentiment-based bias.

### 5.5 Hourly Trading Behavior :

**Plot:** Trading frequency per hour with sentiment split

**Insights:**

- Trading activity spikes during specific hours for both sentiment types.
- Greed periods show more activity during later hours.
- Fear days show flatter distribution, indicating hesitation.

### 5.6 Account-Level Profitability :

**Plot:** Top 10 profitable accounts

**Insights:**

- A small group of trader accounts generated significant profit.

- Some accounts consistently outperformed regardless of sentiment.
- These might represent:
  - experienced traders
  - algorithmic trading systems
  - or high-volume whales

## 5.7 Correlation Between Numeric Variables :

**Plot:** Heatmap

**Insights:**

- Size USD and Size Tokens correlate strongly (as expected).
- Execution Price has low correlation with PnL.
- Closed PnL is weakly correlated with trade size, suggesting skill dominates size.

# 6. Key Insights & Patterns

## 1. Traders take more risks during Greed.

- Bigger trade sizes
- Higher variance in PnL
- More long positions

## 2. Traders become cautious during Fear.

- Smaller trade sizes
- Lower profitability
- Increased short positions
- Reduced activity

## 3. Profitability is sentiment-dependent.

- Greed periods allow higher upside but also greater downside.
- Fear periods compress profit ranges.

## 4. Direction Bias is strong.

- Greed → buy-side dominance
- Fear → short-side preference

## 5. Skilled traders behave differently.

Some accounts generate profit consistently, unaffected by market mood — possibly systematic or experienced traders.

## 7. Limitations

- The dataset does **not include leverage**, so risk-adjusted analysis was limited.
- No information about unrealized PnL or liquidation prices.
- Sentiment data is day-level; minute-level sentiment would give deeper insight.
- Closed PnL does not indicate trade duration.

~Despite these limitations, the analysis still reveals meaningful behavior differences.

## 8. Conclusion

This analysis demonstrates clear behavioral shifts between Fear and Greed market conditions. Traders generally:

- Increase position sizes during Greed
- Take more long positions
- Show higher profit potential
- But also incur larger losses

During Fear, traders:

- Reduce exposure
- Shift toward shorting
- Display cautious PnL patterns

~Understanding these relationships helps build trading strategies aligned with market psychology, enabling better timing, risk management, and position sizing.