Analysis Of Trader Behaviour VS Bitcoin Market Sentiment

• Project Overview

This analysis investigates the relationship between Bitcoin market sentiment (Fear–Greed Index) and trader behaviour on Hyperliquid. We merged daily sentiment with trade-level data to study volume, direction (open/close long/short), realized profitability, and divergence between sentiment and trader actions. The analysis includes data cleaning, merging, EDA, direction & volume analysis, profitability distribution (closedPnL), and divergence detection.

• Project Objective

The objective of this analysis is to understand how market sentiment influences trade behaviour, profitability patterns, and position sizing, and to identify data-backed improvements for smarter trading decisions.

• Tools & Technologies Used

Python, Pandas, NumPy, Jupyter Notebook, Regex cleaning, Feature engineering.

• Future Work

- Developing predictive models for sentiment-based profitability.
- Clustering traders based on behaviour.

• Dataset Summary

This project uses **two datasets** from different sources: one capturing market sentiment and another containing detailed historical trader activity. A summary of both datasets is provided below.

Dataset 1 — Historical Trader Data

- **Total Rows:** ~200,000
- **Total Columns:** 14
- **File Type:** CSV
- **Granularity:** *Each row represents one executed trade (order fill).*
- **Time Span:** Multiple days (timestamped at second/millisecond level)
- **Purpose:** Used to analyze trader behaviour such as direction, volume, profitability, and position closing.

Dataset 2 — Fear & Greed Sentiment Dataset

- **Total Rows:** ~3,000
- **Total Columns:** 4
- **File Type:** CSV
- **Granularity:** *Daily sentiment reading.*
- **Purpose:** Used to quantify market psychology and merge with trading behaviour for divergence analysis

• Data Cleaning And Standardization Using Python

- **Data Loading** : Imported Dataset Using Pandas
- **Initial Exploration** : Used df.info() to check structure and .describe() for summary statistics.

- **Standardization Of Column Names & Removing ALL Whitespaces** : using pandas string methods (.str.lower() , .str.replace() , .str.strip())
- **Data Consistency Check** : Checked the datatypes of all numerical columns and changed for the required data type (Changed Timestamp IST and Date columns into datetime datatype)\
- **Checked For Null Values**.
- **Created a common Column named "only_date_format" in both datasets with datetime datatype for merging both datasets**.
- **Merged both datasets using inner join for advanced EDA**.

• Data Analysis & Finding Insights Using Python

We performed structured analysis in Python (pandas) to answer key business question

1. Market Sentiment Distribution & User-Driven Sentiment Analysis Function

- **EDA Performed:**
- Calculated the percentage of days falling under each sentiment category: *Extreme Fear, Fear, Neutral, Greed, Extreme Greed.*
- A function was built where the user can input a specific sentiment and receive filtered analysis for that sentiment alone.

- **Use Case & Importance:**

- Helps identify **dominant market mood** across the dataset.
- User-level filtering allows traders to analyze **performance patterns under specific sentiment regimes**.
- Supports strategy-building based on how trades behave in *fear-driven* vs *greed-driven* markets.
- Useful for developing **sentiment-aware trading strategies** (e.g., reducing leverage in extreme greed)

2. Distribution of Buy vs Sell Trades

- **EDA Performed:**
- Computed frequency and distribution of buy trades vs sell trades

- **Use Case & Importance:**
- Shows trader's **directional bias** (bullish vs bearish).
- Helps detect **skewed trading behaviour** or over-exposure to one direction.
- Useful for portfolio balancing and for understanding how trade type aligns with market sentiment.

3. Profit–Loss–Neutral Trade Breakdown + Avg Profit/Loss

- **EDA Performed:**
- Total number of **profitable, loss-making, and neutral trades** identified.
- Computed **average profit** and **average loss** for deeper performance measurement

- **Use Case & Importance:**
- Provides a high-level view of **overall trading performance**.
- Identifies whether the strategy is **skewed towards small profits & big losses** (or vice-versa).
- Helps traders evaluate **risk–reward ratio** and refine stop-loss or take-profit levels.

4. Number of Trades per Market Sentiment

- **EDA Performed:**
- Counted how many trades were executed under each market sentiment category (*Fear, Greed, Extreme Fear, etc.*)

- **Use Case & Importance:**

- Shows the trader’s **activity distribution across sentiment conditions**.
- Helps in understanding whether the trader trades **more aggressively in greed-phase** or **more cautiously in fear-phase**.
- Useful for calibrating trading frequency & exposure based on sentiment cycles

5. Profit/Loss/Neutral Trades for Each Sentiment Category

- **EDA Performed:**
- **Mapped profit, loss, and neutral trade counts for each sentiment bucket**

- **Use Case & Importance:**
- Reveals which market sentiment leads to **best performance**.
- Helps identify **weak zones** (e.g., losses occurring mostly during Extreme Greed).
- Critical for designing **sentiment-conditioned strategies**, position sizing, and risk management.

6. Trade Size Analysis by Direction + Filter for Closed vs Active Trades

- **EDA Performed:**
- Calculated **total** and **average** trade sizes for each direction:
  Open Long, Close Long, Open Short, Close Short, etc.
- Added a filter to separate **past traders (closed trades)** vs **current active trades**

- **Use Case & Importance:**
- **Shows how position sizes vary with trade direction.**
- **Helps identify over-leveraging behaviour in long or short trades.**
- **Filtering by active vs closed helps evaluate:**
- **Risk exposure in currently open positions**
- **Historical position sizing patterns**
- **Useful for real-time risk monitoring, margin management, and position optimization.**

- ## Insights

1. Fear-driven market dominates trading conditions

- The majority of days in the dataset fall under **Fear (781 days)** and **Extreme Fear (508 days)**, indicating that nearly half of market activity occurs during negative sentiment phases.

2. Strong trading activity during fear phases

- During **Fear** periods alone, traders placed **61,837 trades** (30,270 buy & 31,567 sell), the highest across all sentiments.
  This shows the trader tends to be **most active during pessimistic market phases**, possibly exploiting volatility or mean-reversal opportunities.

3. Slight bearish bias in overall trading behaviour

- The dataset shows **108,528 Sell trades** vs **102,696 Buy trades**, indicating a moderate preference for short-selling. This suggests the trading strategy is more aligned with **downtrend or correction-based setups**, reflecting a bearish or counter-trend approach.

4. Profitability is high, but risk–reward ratio needs improvement

- Although total **profitable trades (86,869)** significantly outnumber loss-making trades (17,539), the **average loss (₹168.13)** is higher than the **average profit (₹152.48)**.
  This implies:

  - Wins occur more frequently,

  - But losses are **larger per trade**, indicating a **less efficient risk–reward structure** and potential need for tighter stop-loss mechanisms

5. Market activity is concentrated in fear-driven environments

- Fear (78,000+ trades) and Extreme Fear phases show the **highest trading activity** and also deliver **strongest profitability** (26,019 and 7,931 profitable trades respectively).
  This indicates that traders thrive during **high-volatility, pessimistic conditions**, suggesting the strategy may be optimized for fear-led market reversals.

6. Greed does not always translate to higher profits

- While Greed and Extreme Greed phases together contributed **85,000+ trades**, the performance is mixed:
- Greed → **High losses (5,818)**
- Extreme Greed → **Very low losses (2,259)** but **high profit concentration (18,594)**
  This indicates that market exuberance affects behaviour differently—**mild greed induces riskier decisions**, while **extreme greed presents cleaner momentum opportunities.**

7. A slight bearish bias exists, but long setups tend to carry higher capital exposure

- **Sell trades (108,528)** exceed buy trades (102,696), confirming a **small short-selling preference**.
- However, **long trades carry significantly larger capital sizes**:

  - Past traders (closed): Avg long size ≈ **$9,969**, avg short size ≈ **$4,761**
  - Active traders: Avg long size ≈ **$5,003**, avg short size ≈ **$4,483**
    This means traders **prefer short directions**, but the **heaviest capital commitments** are placed into long positions, reflecting a bullish expectation despite bearish activity.

8. Profit frequency is strong, but losses are costlier than wins

- Profitable trades: **86,869**
- Loss trades: **17,539**
- Neutral trades: **106,816**
- Avg Profit = **152**
- Avg Loss = **168.13**
  This shows the system wins often but loses **larger amounts**, creating a **risk–reward imbalance**.
  Optimizing stop-loss levels could significantly improve long-term returns.

9. Sentiment-wise performance reveals clear behavioural patterns

- **Fear → Best performance** (26,019 wins / 3,789 losses)
- **Extreme Fear → Consistent profits** (7,931 wins / 2,475 losses)
- **Extreme Greed → Second-best win ratio** (18,594 wins / 2,259 losses)
- **Greed → High profit but also highest loss count** (19,358 wins / 5,818 losses)
- The data shows losses surge during **Greed**, indicating **risk-taking increases during bullish excitement**, while **discipline is strongest in more extreme sentiment conditions.**

10. Long positions historically carried more exposure, but current open positions show reduced risk appetite

- Past long positions averaged **$9,969**, but active long positions average **$5,003**, showing a **~50% reduction** in active exposure.
  This indicates traders are **reducing leverage and position size recently**, possibly due to shifting volatility or improved risk management.