# Trader Behavior Insights under Market Sentiment Regimes

**Fear vs Greed Analysis using Hyperliquid Trade Data**

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**Datasets:**

- Hyperliquid Historical Trade Data
- Bitcoin Fear & Greed Index

## 1. Executive Summary

This analysis investigates how trader performance and behavior vary across market sentiment regimes—specifically Fear and Greed—using high-frequency trade data from Hyperliquid combined with daily Bitcoin Fear & Greed Index data.

Due to differences in temporal coverage, approximately **17% of trades aligned with available sentiment data**, which is consistent with real-world market datasets. All sentiment-based insights are derived from this aligned subset.

Key findings indicate that:

- **Trader risk-taking increases during Greed**, without a proportional increase in returns.
- **Normalized profitability (PnL per USD)** is more stable during Fear regimes.
- **Top traders outperform consistently across both Fear and Greed**, while bottom traders suffer disproportionately during Greed phases.
- **Contrarian trades** (long during Fear, short during Greed) demonstrate superior risk-adjusted performance.

These findings suggest that sentiment-aware risk control and contrarian positioning may enhance trading strategy robustness in volatile crypto markets.

## 2. Problem Statement & Objective

Crypto markets are highly sentiment-driven, often exhibiting irrational trader behavior during periods of extreme optimism or pessimism.

The objective of this analysis is to:

- Examine how trader profitability, risk behavior, and directional bias vary across Fear and Greed sentiment regimes.
- Identify whether skilled traders maintain performance across sentiment cycles.
- Uncover behavioral patterns that could inform smarter, sentiment-aware trading strategies.

## 3. Dataset Overview

| Aspect | Hyperliquid Trade Data | Bitcoin Fear & Greed Index |
|---|---|---|
| **Purpose** | Capture individual trader behavior and performance at execution level | Capture overall market sentiment on a daily basis |
| **Granularity** | Trade-level (high-frequency) | Daily |
| **Time Coverage** | Intraday, multiple trades per account per day | One sentiment value per calendar day |
| **Primary Entities** | Individual trader accounts | Market-wide sentiment indicator |
| **Key Fields** | account, side, size_usd, closed_pnl, execution_price, timestamp, direction | date, classification, value (numeric index) |
| **Trade Direction Information** | Buy/Sell side, long/short orientation | Not applicable |
| **Risk / Exposure Signals** | Position size (USD), realized PnL | Sentiment intensity via numeric index (0–100) |
| **Nature of Data** | High-frequency, transactional, multi-account trading data | Low-frequency, aggregated sentiment data |
| **Data Volume** | Large-scale (200k+ trades) | Moderate (daily observations) |
| **Preprocessing Applied** | Timestamp standardization, column normalization, exposure-based metrics | Date parsing, sentiment normalization |
| **Sentiment Normalization** | Not applicable | Extreme Fear → Fear, Extreme Greed → Greed |
| **Role in Analysis** | Micro-level trader behavior and performance analysis | Macro-level market sentiment regime classification |

***# Sentiment labels such as Extreme Fear and Extreme Greed were collapsed into Fear and Greed respectively to reduce noise, improve statistical robustness, and ensure sufficient sample sizes for comparative analysis.***

# 4. Data Preparation & Methodology

This section outlines the systematic data engineering and preprocessing steps undertaken to ensure analytical accuracy, reproducibility, and robustness when combining high-frequency trading data with low-frequency market sentiment data.

## Timestamp Normalization and Date-Level Alignment

The Hyperliquid trade dataset contains high-frequency timestamps with multiple trades occurring per account within a single day, while the Fear & Greed Index is published at a daily frequency. To enable meaningful integration of these datasets:

- All trade timestamps were parsed and converted into standardized datetime formats.
- A **date-level trade key (trade_date)** was derived from trade timestamps.
- Sentiment data dates were similarly parsed and aligned to the same calendar date format.
- Trades were merged with sentiment data using the derived trade_date, enabling each trade to inherit the prevailing market sentiment for that day.

This approach ensures consistent temporal alignment between micro-level trading activity and macro-level market sentiment.

## Schema Standardization and Data Consistency

To maintain clean, readable, and error-resistant code throughout the analysis:

- All column names were standardized to **lowercase snake_case** format.
- Inconsistent naming conventions and whitespace in raw columns were normalized.
- This schema standardization improved code reliability, reduced the risk of runtime errors, and ensured scalability for further feature engineering and aggregation.

## Sentiment Coverage Filtering

Due to differences in historical coverage between the two datasets, not all trades could be mapped to a corresponding sentiment value. To preserve analytical validity:

- Trades without available sentiment alignment were **retained in the raw dataset** but **excluded from sentiment-based analyses**.
- Approximately **17% of total trades** aligned with available sentiment data, which is consistent with real-world financial datasets that combine sources with differing temporal spans.
- All conclusions related to Fear vs Greed regimes are explicitly derived from this sentiment-aligned subset.

This filtering prevents distortion of sentiment-based insights while maintaining transparency regarding data coverage.

## Feature Engineering and Risk Normalization

The raw trade data was enriched with derived features designed to enable fair and interpretable performance comparison across traders and sentiment regimes. Key engineered metrics include:

- **Absolute PnL** to capture magnitude of trade outcomes.
- **PnL per USD exposure**, normalizing profitability by capital deployed.
- **Binary win indicator** to measure trade-level success rates.
- **Exposure-based risk proxies**, including normalized absolute PnL and log-scaled position size.

***<u>Since explicit leverage data was unavailable, USD exposure and normalized PnL metrics were used as proxies for risk. This approach ensures fair comparison across trades with varying capital allocation and is commonly used when leverage information is not directly observable.</u>***

## Reproducibility and Analytical Discipline

All preprocessing steps were implemented programmatically within Google Colab notebooks, ensuring:

- Full reproducibility of results
- Clear separation between raw data and analysis-ready datasets
- Compatibility with downstream visualization and aggregation workflows

This disciplined approach establishes a reliable foundation for sentiment-driven behavioral analysis and strategic insight extraction.

# 5. Feature Engineering

To enable fair, interpretable, and sentiment-aware analysis, the raw trade data was enriched with a set of engineered features designed to capture profitability, risk exposure, and directional behavior at the trade level.

## Profitability Metrics

The following performance indicators were constructed to normalize outcomes across trades of varying sizes:

- **Absolute PnL**
  Measures the magnitude of profit or loss per trade, independent of direction. This metric captures outcome intensity and is useful for assessing risk exposure.
- **PnL per USD Exposure**
  Calculated as closed PnL divided by position size in USD, this metric normalizes profitability by capital deployed. It enables fair comparison across trades and traders with different position sizing strategies.
- **Win Indicator**
  A binary indicator denoting whether a trade closed with positive PnL. This feature supports win-rate calculations and behavioral comparisons across sentiment regimes.

## Risk Proxies

Due to the absence of explicit leverage information, exposure-based proxies were employed:

- **Normalized Risk Proxy**
  Defined as absolute PnL divided by USD position size, this metric approximates the volatility of outcomes relative to exposure.
- **Log-Scaled Position Size**
  A logarithmic transformation of USD exposure was applied to stabilize the distribution of trade sizes and reduce sensitivity to extreme values.

These proxies collectively allow risk comparison across sentiment regimes without relying on unavailable leverage data.

## Directional Indicators

To analyze positional bias and crowd behavior:

- Trades were classified as **long (buy)** or **short (sell)**.
- Binary indicators were created to represent long and short positioning.
- Directional features were later evaluated jointly with sentiment to assess crowd alignment and contrarian behavior

# 6. Fear vs Greed Analysis

This section examines how trader behavior and performance differ under distinct market sentiment regimes.

## Aggregate Performance Comparison

Aggregate statistics reveal that:

- **Average PnL during Greed periods appears marginally higher**; however, this increase is largely driven by a small number of large positive outcomes.
- **Median PnL and win rates do not improve proportionally during Greed**, suggesting that higher average profits are accompanied by increased volatility.
- **Normalized returns (PnL per USD exposure) are more stable during Fear regimes**, indicating more disciplined capital deployment.

These findings suggest that Greed regimes encourage increased risk-taking without consistently improving risk-adjusted returns.

## Distributional Insights

Distributional analysis provides deeper insight beyond averages:

- PnL distributions during Greed exhibit **heavier downside tails**, indicating a higher frequency of large losses.
- Fear regimes show **tighter PnL distributions**, reflecting controlled risk and reduced variance in outcomes.
- When normalized by exposure, Fear-period trades demonstrate more consistent performance across the distribution.

This indicates that trader behavior during Fear is generally more cautious and systematically risk-aware.

## Directional Bias under Sentiment

Directional analysis reveals a clear behavioral pattern:

- During Greed periods, traders exhibit a pronounced **long bias**, aligning with prevailing bullish sentiment.
- These sentiment-aligned long positions **underperform relative to contrarian positions**, particularly when evaluated on normalized returns.
- This suggests that crowd-following behavior during Greed often leads to suboptimal trade timing.

## 7. Trader Skill Analysis

- Traders were segmented into **top, middle, and bottom groups** based on cumulative realized PnL.
- **Top traders** maintain positive normalized returns across both Fear and Greed regimes.
- Performance consistency across sentiment regimes indicates **sentiment-robust trading skill**.
- **Bottom traders** experience disproportionately larger losses during Greed periods.
- Elevated losses during Greed suggest **overconfidence, aggressive positioning, and weaker risk control**.

## 8. Contrarian Behaviour Analysis

- Contrarian trades are defined as:
  - **Long positions during Fear**
  - **Short positions during Greed**
- Contrarian trades exhibit **higher normalized returns** compared to sentiment-aligned trades.
- Win rates for contrarian trades are consistently superior across sentiment regimes.
- Results indicate that **crowd-following behavior** during extreme sentiment often leads to **suboptimal trade timing**.
- Disciplined contrarian positioning provides **more stable risk-adjusted performance**.

## 9. Limitations

- Only ~**17% of total trades** align with available sentiment data due to differing dataset coverage.
- **Explicit leverage data is unavailable**, requiring reliance on exposure-based risk proxies.
- Order-book dynamics and market microstructure information are not included.
- Findings should be interpreted as **behavioral and comparative insights**, not precise causal estimates.

## 10. Strategic Implications & Future Work

- Sentiment-aware **risk throttling** can mitigate losses during Greed regimes.
- Contrarian positioning can improve **risk-adjusted performance consistency**.
- Future extensions may include:
  - Real-time sentiment integration
  - Trader behavior clustering
  - Reinforcement learning–based adaptive strategies

## 11. Conclusion

- Market sentiment has a **measurable impact on trader behavior and performance**.
- Increased optimism is associated with **higher risk-taking without proportional returns**.
- Traders who maintain **disciplined risk management** and adopt **contrarian strategies** exhibit more resilient performance across market regimes.
- These findings support the development of **sentiment-aware trading systems** in crypto markets.