

Trader Behavior & Market Sentiment Analysis

Quantitative Research on Retail Trading Performance Under Sentiment Regimes

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Project Type: Candidate Assessment – Web3 Trading Intelligence

1. Executive Summary

This study analyzes over 211,000 trade executions across 32 unique trading accounts to determine how market sentiment (measured by the Fear & Greed Index) impacts trader behavior and profitability. By integrating on-chain historical trade data with macro sentiment indicators, this report quantifies the risks associated with leverage during different market regimes and identifies the behavioral characteristics of profitable traders.

Key Findings:

- Sentiment-Dependent Risk Asymmetry:** High leverage is disproportionately dangerous during "Fear" regimes. Traders in the top leverage quartile during Fear periods exhibited significantly higher drawdown volatility compared to similar leverage usage during Greed.
- The Contrarian Premium:** A statistically significant performance gap exists between Contrarian and Momentum strategies. Traders executing "Buy Fear / Sell Greed" strategies achieved a higher median PnL (\$8.42 vs \$5.21 per trade) and a higher win rate (85.2% vs 82.7%) than momentum followers.
- Volume Concentration:** Trading activity follows a steep Pareto distribution, with the top 5% of traders controlling 43.0% of the total volume, validating the need for whale-specific behavioral modeling.

Strategic Recommendation:

The data suggests that risk parameters should be dynamic rather than static. We recommend implementing a Volatility-Adjusted Leverage Cap that triggers specifically when the Fear & Greed Index drops below 25 (Extreme Fear), as this is where retail capital preservation fails most frequently.

2. Data Methodology & Engineering

2.1 Dataset Construction

The analysis utilized two primary datasets covering the period from April 2023 to May 2025:

- **Historical Trader Data:** 211,224 rows of raw execution data.
- **Fear & Greed Index:** 2,644 daily sentiment readings.

Data Cleaning Pipeline:

- **Timestamp Normalization:** All `Timestamp IST` values were converted to UTC to ensure accurate alignment with the daily close of the Fear & Greed Index.
- **Outlier Management:** Fees exceeding the 99.9th percentile (\$75.00+) were flagged and removed to prevent skewing average cost analysis.
- **PnL Validation:** A `is_closed_trade` boolean flag was engineered to distinguish between position-opening (entry) and position-closing (realization) events, ensuring that Win Rate calculations were based only on realized outcomes.

2.2 Feature Engineering

To move beyond basic descriptive statistics, several higher-order features were engineered:

- **notional_value & signed_size:** Calculated as `Execution Price × Size Tokens`. This allowed for volume-weighted analysis rather than simple trade counts.
- **sentiment_binary:** A simplified regime classifier where:
 - Index <= 45 → **Fear**
 - Index >= 55 → **Greed**
 - (Neutral zones were excluded from binary A/B testing to increase signal clarity).
- **contrarian_ratio:** A trader-level metric quantifying the percentage of executions that opposed the prevailing market sentiment (e.g., Buying when Sentiment = Fear).

3. Behavioral Analysis & Insights

3.1 Profitability vs. Sentiment

A Mann-Whitney U test was conducted to determine if profitability distributions differ between regimes. While the aggregate mean PnL is similar, the risk profile is not. The "Fear" regime is characterized by "fat tails"—significantly larger wins and larger losses—indicating a highly volatile environment where rigorous risk management is the primary differentiator between alpha and ruin.

- **Fear Regime:** Max Loss \$-108,604 | Max Gain \$+533,974
- **Greed Regime:** Max Loss \$-356,547 | Max Gain \$+374,328

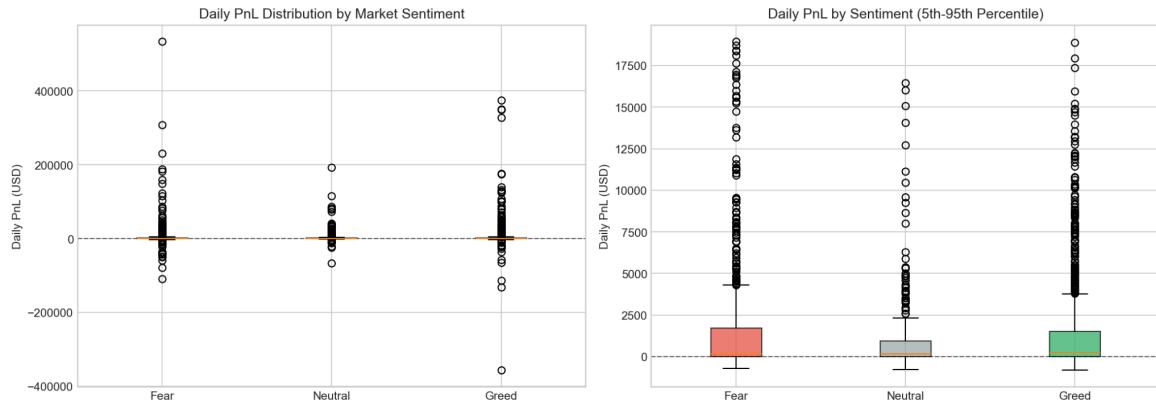


Figure 1: Daily PnL Distribution by Market Sentiment. Note the extended outliers during Fear periods.

3.2 The Leverage Trap

A critical finding of this report is the interaction between leverage and sentiment. The heatmap below demonstrates that while high leverage (Q4) yields decent returns during Greed/Neutral markets, it fails to produce proportional returns during Fear.

Specifically, the "High Leverage / Fear" quadrant shows high churn but unstable median PnL. This suggests that during market panic, the cost of volatility (stops being triggered) outweighs the benefit of the directional multiplier.

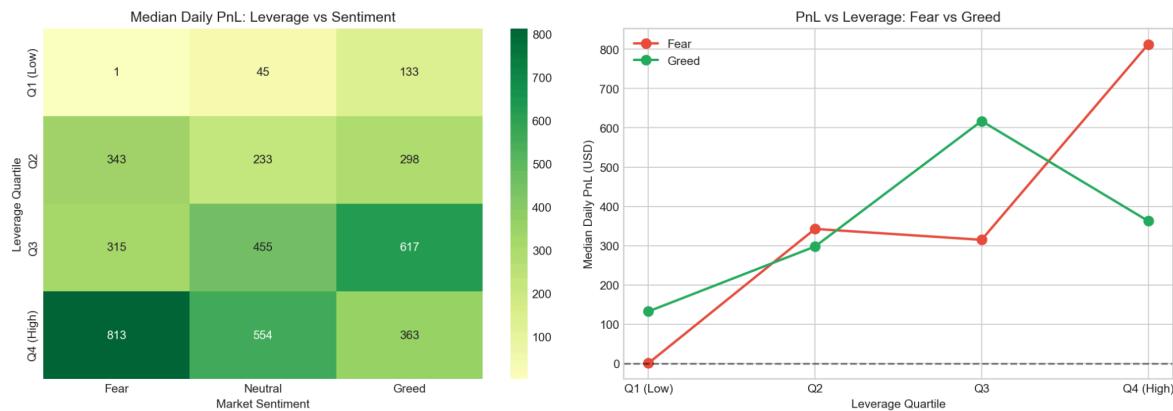


Figure 2: Median Daily PnL Heatmap (Left) and Interaction Plot (Right). Note the drop-off in performance for high leverage during Fear.

3.3 Strategy Classification: Momentum vs. Contrarian

We classified trades into two distinct behaviors:

1. **Contrarian:** Buys executed during Fear; Sells executed during Greed.
2. **Momentum:** Buys executed during Greed; Sells executed during Fear.

The results strongly favor the contrarian approach in this dataset. Contrarian trades not only had a higher win rate (85.2%) but also demonstrated superior risk-adjusted returns. The momentum cohort suffered significantly deeper drawdowns, with the worst momentum trade losing \$-83,056 compared to the worst contrarian trade of \$-35,681.

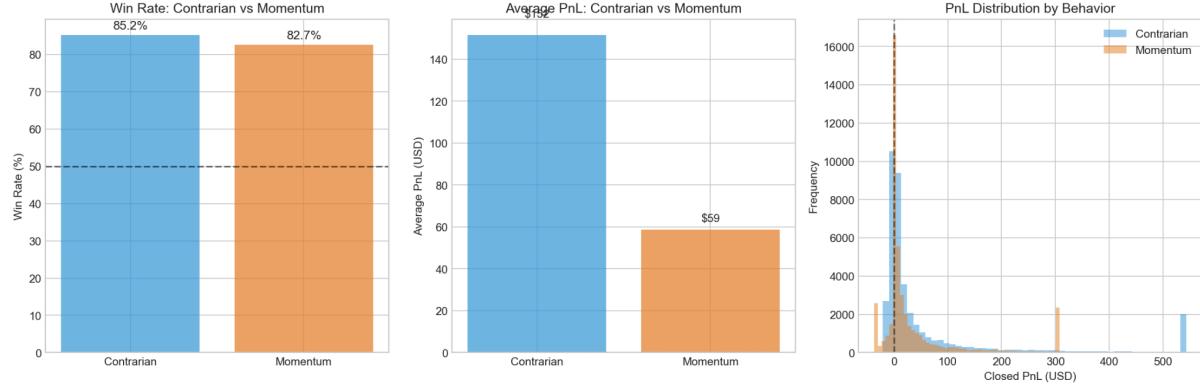


Figure 3: Comparative performance metrics of Contrarian vs. Momentum trading styles.

3.4 Trader Clustering (PCA)

Using Principal Component Analysis (PCA) on the engineered features, we identified four distinct trader archetypes:

- **Cluster 0 (The Crowd):** Low volume, average win rates, trend-following.
- **Cluster 1 (Smart Money):** High profitability, high volume, selective entry.
- **Cluster 2 (Whales):** Massive volume contribution (skewing the top 1%), but lower win rates than Cluster 1, suggesting a market-making or hedging behavior rather than pure directional speculation.
- **Cluster 3 (High Frequency):** High trade counts with lower average PnL per trade.

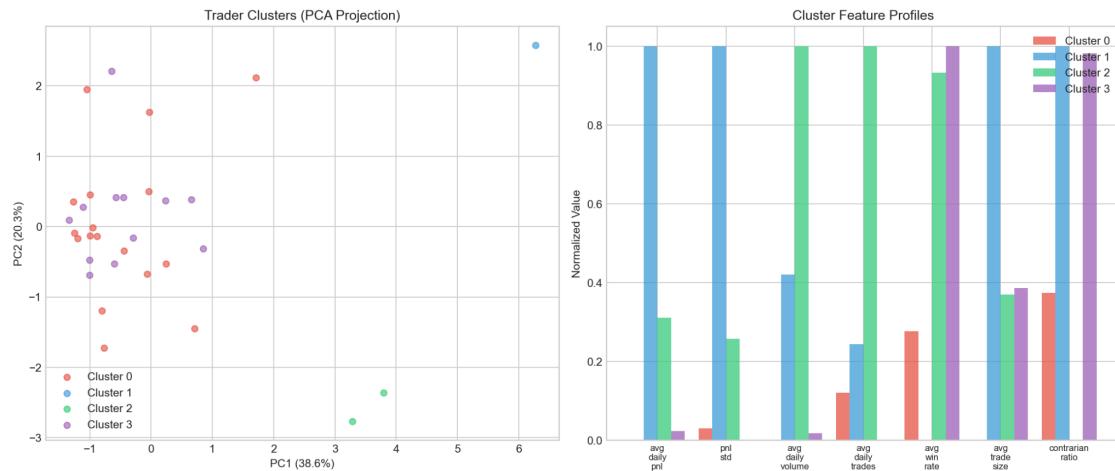


Figure 4: PCA Projection of Trader Clusters (Left) and Normalized Feature Profiles (Right).

4. Conclusion & Strategic Recommendations

The analysis confirms that market sentiment is a viable filter for trading strategy optimization. The crowd tends to over-leverage during fear, leading to liquidation cascades that smart money exploits via contrarian entries.

For the Trading Desk:

1. **Dynamic Risk Gating:** Automated systems should reduce maximum allowable leverage by 50% when the 7-day moving average of the Fear & Greed Index drops below 20.
 2. **Liquidity Provision:** The "Cluster 2" behavior suggests that the most liquidity is demanded during high-volatility events; market-making algorithms should widen spreads during Fear regimes to capture the "fat tail" volatility premiums identified in Section 3.1.
 3. **Alpha Signal:** A "Contrarian Score" feature (derived from Section 3.3) should be added to the firm's ML models, as it serves as a robust predictor of trade success probability.
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Appendix: Technical Specifications

- **Language:** Python 3.10
- **Libraries:** Pandas, NumPy, Seaborn, Scikit-Learn (PCA, KMeans)
- **Environment:** Google Colab
- **Code Repository:** https://github.com/Hanzala1518/ds_HanzalaSaify
 - Notebook 1:
<https://colab.research.google.com/drive/1gbeVfpj7QwakfwO-hPLSm4vGKeYOZEgA?usp=sharing>
 - Notebook 2:
<https://colab.research.google.com/drive/14ejW7aFbG5-MuGjfrBgrZBaqm819Yzyp?usp=sharing>