

Trader Behavior Analysis Under Market Sentiment Regimes

Candidate: Sharanya Rao

Role: Junior Data Scientist – Trader Behavior Insights

Company: Primetrade.ai

Date: 30/12/2025

Objective

The objective of this analysis is to understand how trader performance and behavior vary under two different Bitcoin market sentiment regimes, **Fear** and **Greed**. By combining historical trader-level data with market sentiment indicators, the goal is to uncover behavioral patterns, risk characteristics, and trader profiles that can inform smarter trading strategies and capital allocation.

Datasets Used

1. Different Sentiment Dataset:

- Daily sentiment labels: Fear, Extreme Fear, Neutral, Greed, Extreme Greed
- Simplified into two regimes: Fear and Greed

2. Historical Trader Data:

- Trade-level data including:
 - Trader account
 - Timestamp
 - Closed PnL
 - Trade size (USD)

Data Preparation Summary

- Trade timestamps were converted to dates to align with daily sentiment.
- Extreme Fear and Extreme Greed were merged into Fear and Greed respectively.
- Neutral sentiment was excluded to maintain clear regime comparison.
- Extreme outliers were retained but additionally analyzed using trimmed views for robustness.

Methodology

The analysis was conducted at two levels:

Sentiment-Level Analysis

- Aggregate performance metrics were computed for Fear and Greed regimes:
 - Total PnL
 - Average PnL
 - Trade count
 - Average trade size
 - Volatility (standard deviation)
 - Approximate risk-adjusted return (Sharpe proxy)

Trader-Level Analysis

- Trader performance was analyzed separately under Fear and Greed.
- Traders were classified based on relative performance:
 - Fear-Resilient (Contrarian) traders
 - Greed-Optimized (Trend-Following) traders
- Top-performing traders were identified per sentiment regime.

Key Findings

Sentiment-Level Insights

- Greed regimes generate higher total and average PnL, but with elevated volatility.
- Fear regimes exhibit larger average trade sizes, suggesting selective but higher-conviction positioning.
- Risk-adjusted performance (Sharpe proxy) is comparable across regimes, with slight advantages during Greed.

Distributional Behavior

- PnL distributions in both regimes show heavy tails and frequent outliers.
- Median PnL is close to zero, reflecting high-frequency or low-margin trading behavior.
- These characteristics are consistent with real-world crypto trading environments.

Trader Behavior Patterns

- Trader performance is not uniform across sentiment regimes.
- A subset of traders consistently outperforms during Fear, indicating contrarian or disciplined strategies.
- Other traders perform significantly better during Greed, aligning with momentum-based or trend-following behavior.

Trader Personas Identified

Trader Type	Description
Fear-Resilient (Contrarian)	Traders who outperform during Fear, often using disciplined risk management and selective entries
Greed-Optimized (Trend-Following)	Traders who benefit from high-liquidity, momentum-driven market conditions

These personas can be used to tailor strategy allocation depending on prevailing market sentiment.

Strategic Implications

Based on the analysis, the following strategies are recommended:

- **Sentiment-Aware Allocation**
Allocate more capital to Fear-Resilient traders during downturns and Greed-Optimized traders during bullish phases.
- **Risk Controls During Greed**
Implement leverage and drawdown limits to manage volatility during Greed regimes.
- **Trader Profiling for Platform Intelligence**
Use trader sentiment profiles to enhance leaderboard rankings, copy-trading recommendations, or risk dashboards.

Limitations & Future Work

Limitations

- Sentiment is treated as a daily, market-wide indicator.
- Sharpe ratio is approximated and not annualized.
- Intraday sentiment shifts are not captured.

Future Enhancements

- Multi-class sentiment modeling (Fear / Neutral / Greed)
- Trader clustering using behavioral metrics
- Regime-aware performance forecasting
- Time-series analysis of trader adaptability

Conclusion

This analysis demonstrates that market sentiment plays a significant role in shaping trader behavior, profitability, and risk. By identifying sentiment-dependent trader profiles and understanding regime-specific dynamics, trading platforms can design smarter, more adaptive strategies that improve both performance and risk management.