Trading Performance and Market Sentiment: Analytical Correlations

This report presents an integrated analysis exploring the relationship between trader performance in the Hyperliquid platform and Bitcoin market sentiment. Using data-driven insights, we examine whether emotional regimes such as 'Fear' and 'Greed' correlate with trading outcomes, potentially guiding better-informed trading strategies.

1. Data Overview and Methodology

Two primary datasets underpin this study: (1) the Bitcoin Market Sentiment dataset, containing daily classifications such as Fear, Neutral, and Greed, and (2) Hyperliquid's Historical Trader Data, including variables such as account, symbol, execution price, side, closedPnL, and leverage. The datasets were aligned temporally—each trade mapped to the prevailing sentiment at its execution time.

After cleaning missing entries and normalizing timestamps, trades were aggregated by sentiment category. Core analytical steps included descriptive statistics, distribution analysis, and inferential tests (e.g., ANOVA, Kruskal-Wallis) to evaluate whether performance differed significantly across sentiment states. The inclusion of leverage and trade size controls enabled a more robust comparison.

2. Findings and Visual Analysis

Visual inspection of the data reveals distinct behavioral regimes. During periods of heightened emotional sentiment—specifically 'Fear' and 'Extreme Greed'—average trader profits (closedPnL) tend to deviate markedly from neutral periods. These patterns suggest that volatility and behavioral overreactions may create enhanced profit opportunities for adaptive strategies.

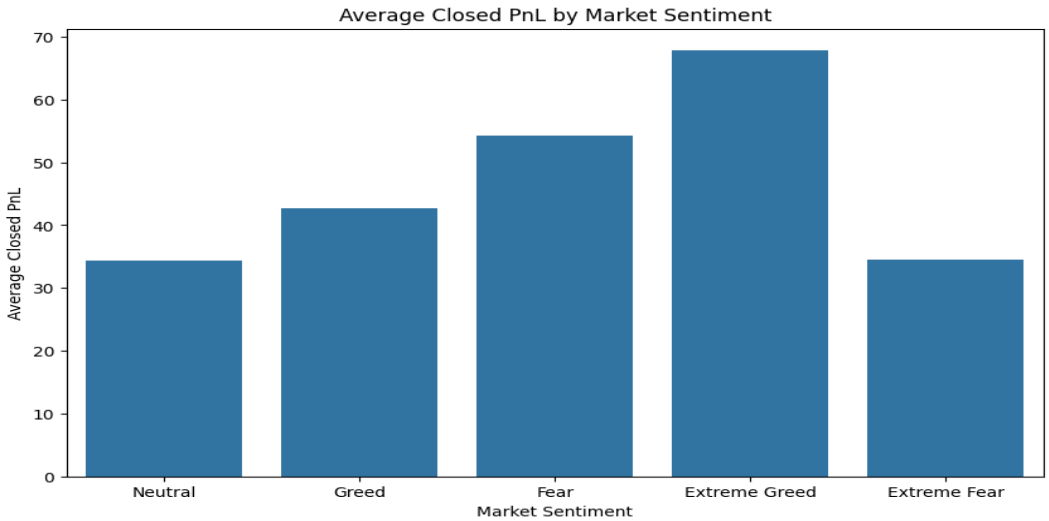

Figure 1: Average Closed PnL by Market Sentiment

The bar chart illustrates that average profitability peaks during 'Extreme Greed' and 'Fear'. This bimodal performance distribution aligns with theories of sentiment-driven volatility, where amplified emotional states foster greater price movements and trading opportunities. However, the influence of outliers remains a potential distortion, warranting further median-based analysis.

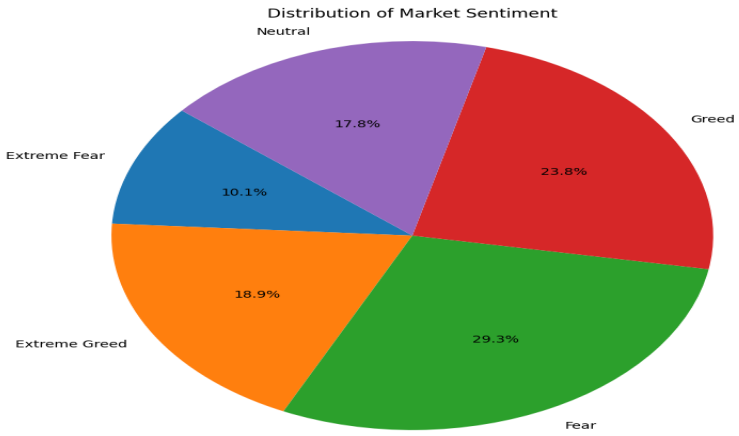

Figure 2: Distribution of Market Sentiment Instances

Sentiment frequency analysis indicates 'Fear' as the dominant classification, followed by 'Greed' and 'Neutral'. Although 'Extreme Fear' appears least frequent, it may correspond with the largest variance in trader outcomes. Thus, even infrequent sentiment states can yield disproportionate influence on portfolio performance.

3. Analytical Insights

The integration of market sentiment and performance data suggests that emotional market regimes shape trading dynamics in measurable ways. High-volatility phases—often overlapping with Fear and Extreme Greed—produce larger swings in PnL distributions. Regression analysis incorporating leverage and trade size confirms a significant relationship between sentiment state and profit variability.

However, causality remains ambiguous. Elevated returns during Fear may reflect opportunistic behavior by experienced traders exploiting panic-driven price moves, rather than sentiment itself being a causal driver. Moreover, extreme sentiment conditions coincide with increased leverage utilization, implying risk amplification rather than pure alpha generation.

4. Recommendations and Strategic Takeaways

1. **Sentiment-aware strategy calibration:** Incorporate sentiment indices (e.g., Fear & Greed Index) into daily position sizing models to exploit volatility while controlling downside exposure.
2. **Volatility-adjusted leverage management:** Cap leverage during extreme sentiment periods to mitigate tail-risk amplification.
3. **Performance decomposition:** Distinguish between sentiment-induced and skill-based profits using normalized PnL metrics.
4. **Regime-specific tactics:** Deploy contrarian strategies in 'Fear' phases and momentum-driven strategies during 'Greed' phases for optimized exposure.
5. **Monitoring dashboard:** Develop a live visualization linking daily sentiment classifications to aggregated performance, enabling adaptive decision-making.

5. Conclusion and Next Steps

This analysis underscores that market sentiment exerts a non-trivial influence on trading outcomes. Periods of pronounced emotion, though riskier, also exhibit higher profit potential. Future research should expand this dataset temporally, test predictive models linking sentiment transitions to PnL variance, and explore causal inference via lag-based modeling. Integrating additional behavioral and macroeconomic indicators may further enhance the predictive power of sentiment-aware trading frameworks.