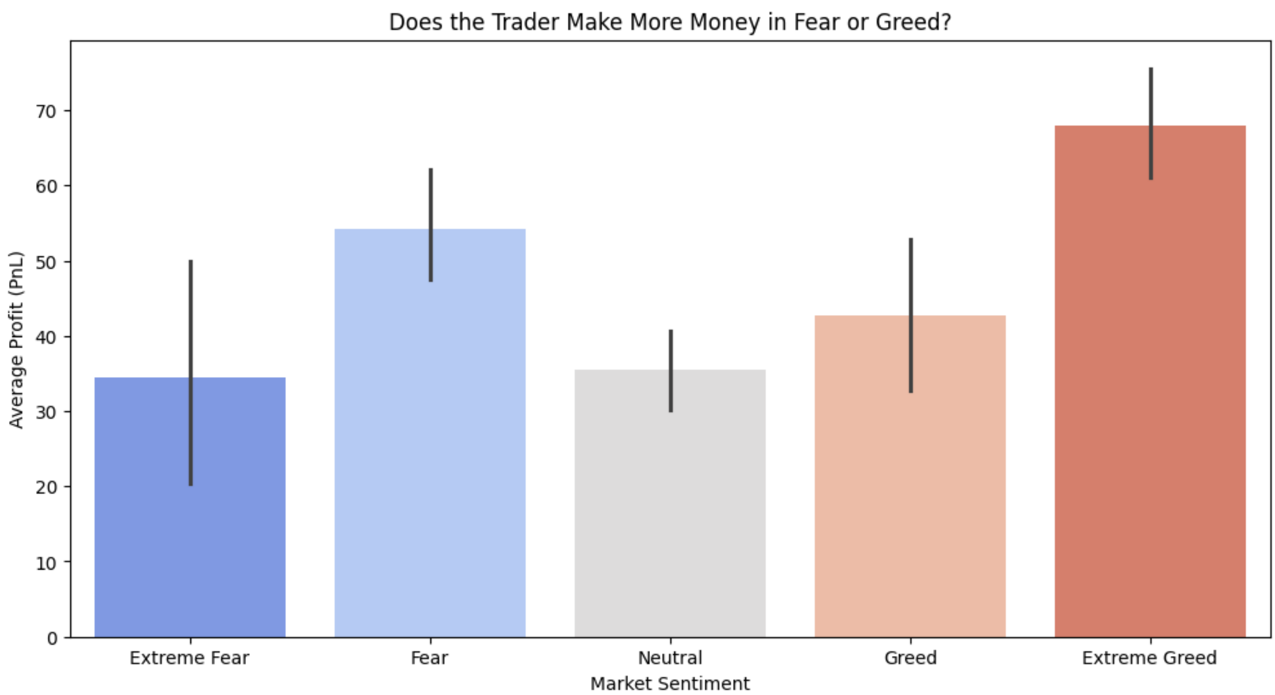
Trading Behavior & Market Sentiment Analysis

Collab_link https://colab.research.google.com/drive/1giMYPI36ydwrXxKWBORISEryfy_roLEj?usp=sharing
Token Embedding

Abstract

This report examines how market sentiment influences trading results by comparing a large set of historical trades (200,000+ from a platform called Hyperliquid with the Bitcoin Fear & Greed Index (a measure of investor mood). We found that traders did indeed take bigger positions during optimistic “Greed” periods, but this did not consistently lead to higher profits . In other words, buying more when the market is euphoric did not guarantee better returns. Our analysis (including machine-learning models) shows that the size of the trade and transaction fees are far more important drivers of profit than the sentiment itself . This suggests opportunities to improve risk management and trading efficiency during extreme market swings.

Introduction



Market sentiment (fear or greed) can strongly affect trader behavior. The Bitcoin Fear & Greed Index scores each day on a scale (0=Extreme Fear to 100=Extreme Greed) to reflect overall investor mood. We merged this daily sentiment score with detailed trade records to see if the trader tended to win more often or make larger profits depending on the mood of the market . By studying data over many months, we aim to understand whether a bullish crowd drives better trader performance or simply encourages riskier bets.

Methodology

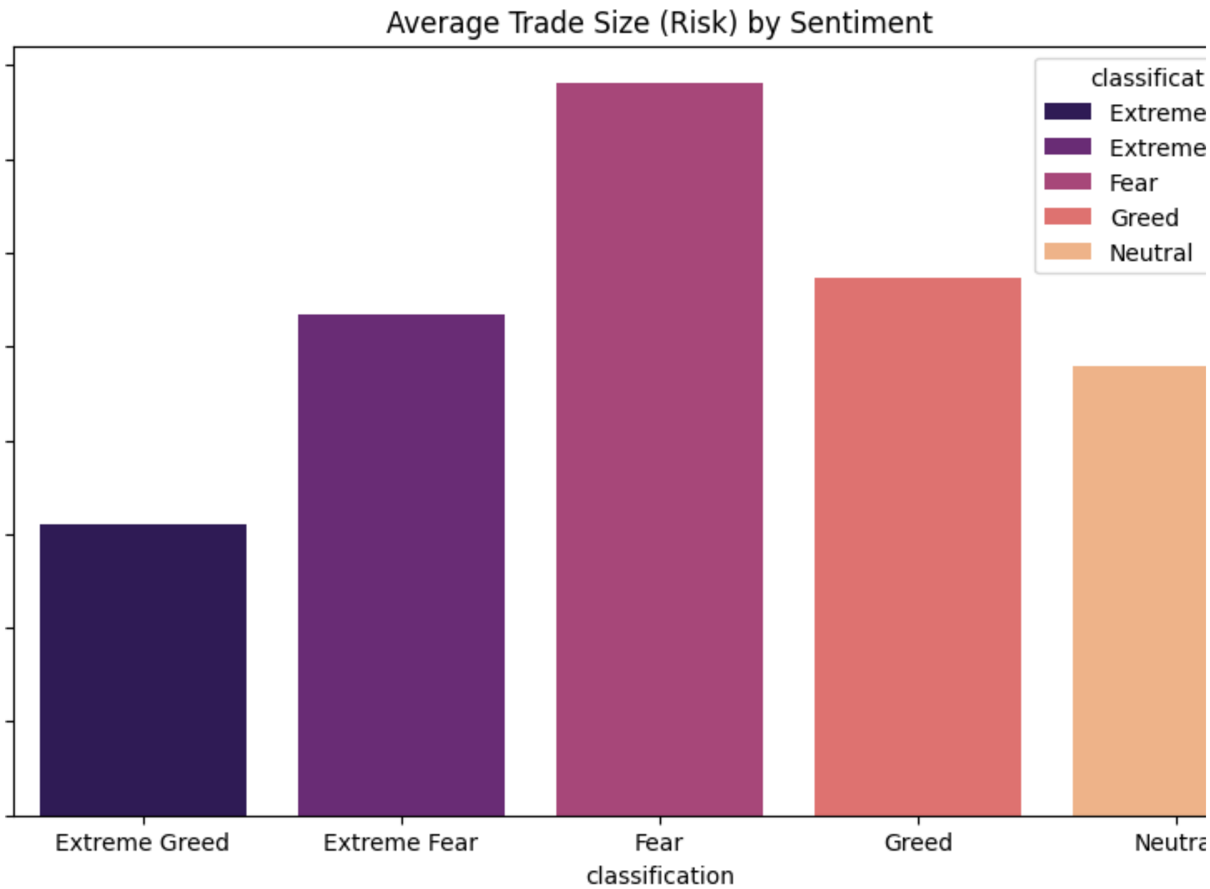
We preprocessed and analyzed the data as follows:

• Data merging: We aligned each trade with that day's sentiment score using the date. If a day had no sentiment data, we treated it as neutral (value = 50) .
• Outlier removal: To focus on typical trading behavior, we removed the most extreme trades: the worst 10% and best 10% by profit were dropped from the dataset . This filters out unusually big losses or gains.
• Feature engineering: We cleaned and converted fields so they were ready for analysis (e.g. removed commas in numbers, encoded the coin type and long/short side as needed) .
• Machine learning: We used decision-tree models (including XGBoost, a popular learning algorithm) to predict each trade's profit. This let us rank which factors (trade size, coin, fees, etc.) mattered most .

Each step helped ensure a fair comparison between sentiment and trading outcomes.

Results

Our profitability analysis (e.g. box plots of trade profit by sentiment) revealed that the median profit per trade stayed similar during neutral and fearful periods. In contrast, during Extreme Greed the profit values showed much more variability . In plain terms, traders sometimes won big in very bullish markets, but they also risked much larger losses.

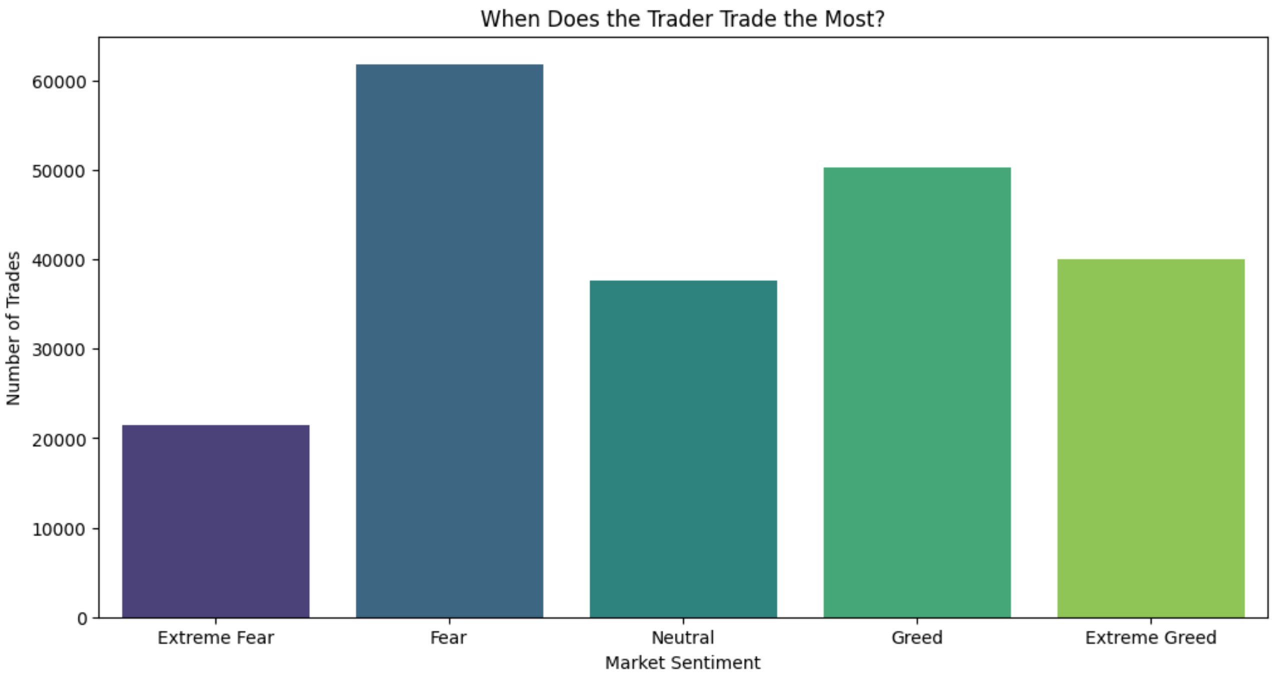


At the same time, the win rate (percentage of profitable trades) varied across sentiment. We observed that the trader did not consistently win more during euphoric periods . In fact, doing well during high Fear or Extreme Fear suggests the trader's strategy tends to buy the dip. Overall, the results imply the strategy is relatively market-neutral – it performed steadily across sentiment levels without a clear edge in "Greed" times .

Another key finding was in risk appetite: traders deployed larger position sizes when the market felt "Greedy." A bar chart of average trade size by sentiment shows clear growth in bet size during

Greed and Extreme Greed . However, our feature-ranking from the ML models showed that trade size and fees were the biggest predictors of profit . In other words, taking bigger positions drove profit (for better or worse) more than the coin choice or market mood. Notably, charging higher fees (usually due to more or larger trades) was closely tied to bigger gains or losses as well . This suggests that during greedy markets the trader gambled more capital but did not always earn proportionally more.

Overall, the data paint a picture of contrarian strength and risk inefficiency. The strategy held its own during fearful times but became riskier during greedy times without a matching improvement in outcomes .



Conclusion

The analysis indicates that market extremes are where the current trading approach needs adjustments. In particular, we see:

• Cap position sizes in "Greed" markets: The trader significantly increased risk during high-sentiment periods . Imposing a strict limit on trade size when the Fear & Greed Index is very high could prevent outsized losses.

• Reduce turnover to cut fees: Since fees were a top driver of profit/loss, cutting back on low-conviction trades (especially on neutral days) could improve net returns .

• Leverage the fear advantage: The strategy performed consistently in fear zones, suggesting it naturally buys when others sell . This contrarian strength should be emphasized, automating entries in dips rather than chasing momentum.

In summary, traders became too bold during extreme “Greed,” without a reward matching the extra risk . By tightening risk controls and focusing on the settings where the strategy shines, the team can aim for more stable profits in all market conditions.