Trade Behaviour Analysis

Impact of Market Sentiment on Trading Performance

Report By - Avdhoot Nakod

Summary

The comprehensive analysis examines the relationship between cryptocurrency market sentiment (Fear & Greed Index) and trading performance on the Hyperliquid platform. By analyzing **211,224 trading transactions** merged with historical sentiment data spanning 6+ years, we uncovered statistically significant patterns that demonstrate how market psychology influences trading outcomes.

- **Key Insight**:

Short positions during "Extreme Greed" periods generated the highest returns ($114.58 average PnL), suggesting contrarian strategies outperform in euphoric markets.

- **Strategic Findings :**

"Fear" sentiment periods showed the largest trade volumes ($7,816 average), indicating institutional or informed trader capitalize on market fear with higher conviction.

Dataset Overview:

The analysis utilized two primary datasets integrated through temporal alignment

Total Trades Analyzed	Sentiment Data Points	Time Period	Sentiment Categories
211,224	**2,500+**	**6+ Years**	**5**
Hyperliquid Platform	Daily Fear & Greed Index	2018 - 2024	Extreme Fear → Extreme Greed

Data Source:

Dataset	Key Features	Records
Hyperliquid Trader Dataset	Account, Coin, Price, Size, PnL, Side, Timestamp, Fees	211,224
Feargreed Dataset	Timestamp, Sentiment Value (0-100), Classification, Date	2500+

Data Preprocessing Steps

- Converted timestamp formats to datetime objects for temporal alignment
- Normalized dates to daily granularity (removed time component)
- Performed left join to merge trader data with sentiment classifications
- Handled missing values (only 6 records with unmatched dates)
- Validated data integrity across 211,218 successfully merged records

Analytical Methodology

Research Approach :

This analysis employed a multi-faceted approach combining exploratory data analysis, statistical hypothesis testing, and visual analytics

- **Exploratory Data Analysis (EDA) -**
    - Univariate and bivariate analysis of sentiment distribution, PnL patterns, and trading volumes
- **Statistical Testing -**
    - Kruskal-Wallis H-test for non-parametric comparison across sentiment groups
- **Post-hoc Analysis -**
    - Dunn's test with Bonferroni correction for pairwise sentiment comparisons
- **Segmentation Analysis -**
    - Performance comparison across long/short positions and sentiment states
- **Distribution Analysis -**
    - Violin plots and box plots for understanding PnL variability
- **Concentration Analysis -**
    - Pareto analysis for identifying top-performing accounts

Technical Stack :

- Python
- Pandas
- Matplotlib
- Seaborn
- Scikit learn
- Scipy
- Google Colab

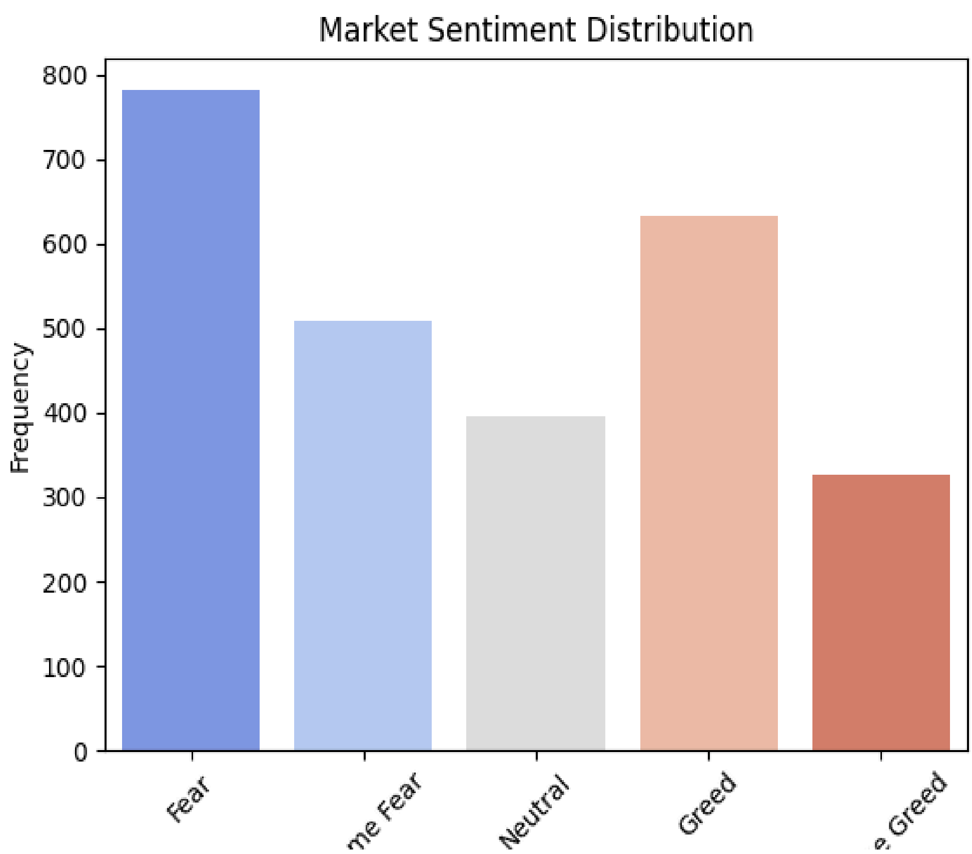
Key Findings & Insights

Market Sentiment Distribution:

Sentiment Category	Frequency	Percentage	Trading Days
Fear	61,837 trades	29.3%	~550 days
Greed	50,303 trades	23.8%	~460 days
Extreme Greed	39,992 trades	18.9%	~365 days
Neutral	37,686 trades	17.8%	~345 days
Extreme Fear	21,400 trades	10.1%	~195 days

Critical Insight:

The market spent nearly 40% of time in "Fear" or "Extreme Fear" states, yet these periods represent only 39.4% of total trades, suggesting traders reduce activity during fearful markets despite potential opportunities.

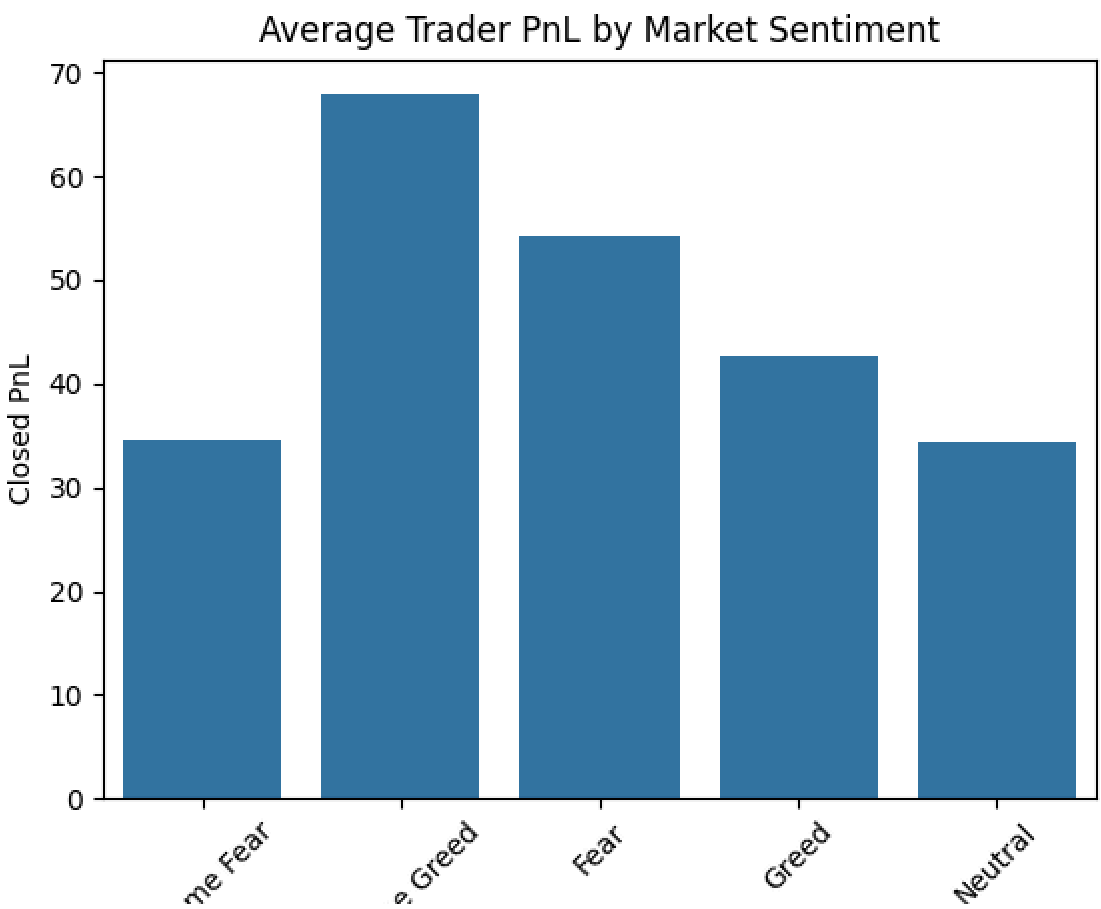


Profitability Analysis by Sentiment:

Sentiment	Avg PnL	Avg Trade Size (USD)	Avg Fee	Relative Performance
Extreme Greed 🏆	$67.89	$3,112.25	$0.68	+97.9% vs Neutral
Fear	$54.29	$7,816.11	$1.50	+58.3% vs Neutral
Greed	$42.74	$5,736.88	$1.25	+24.6% vs Neutral
Extreme Fear	$34.54	$5,349.73	$1.12	+0.7% vs Neutral
Neutral	$34.31	$4,782.73	$1.04	Baseline

Counter-intuitive finding:

"Extreme Greed" periods showed highest profitability despite smaller trade sizes, suggesting skilled traders capitalize on momentum or execute contrarian strategies during euphoric markets. The 2.5x larger trade sizes during "Fear" periods indicate institutional-level conviction during market downturns.

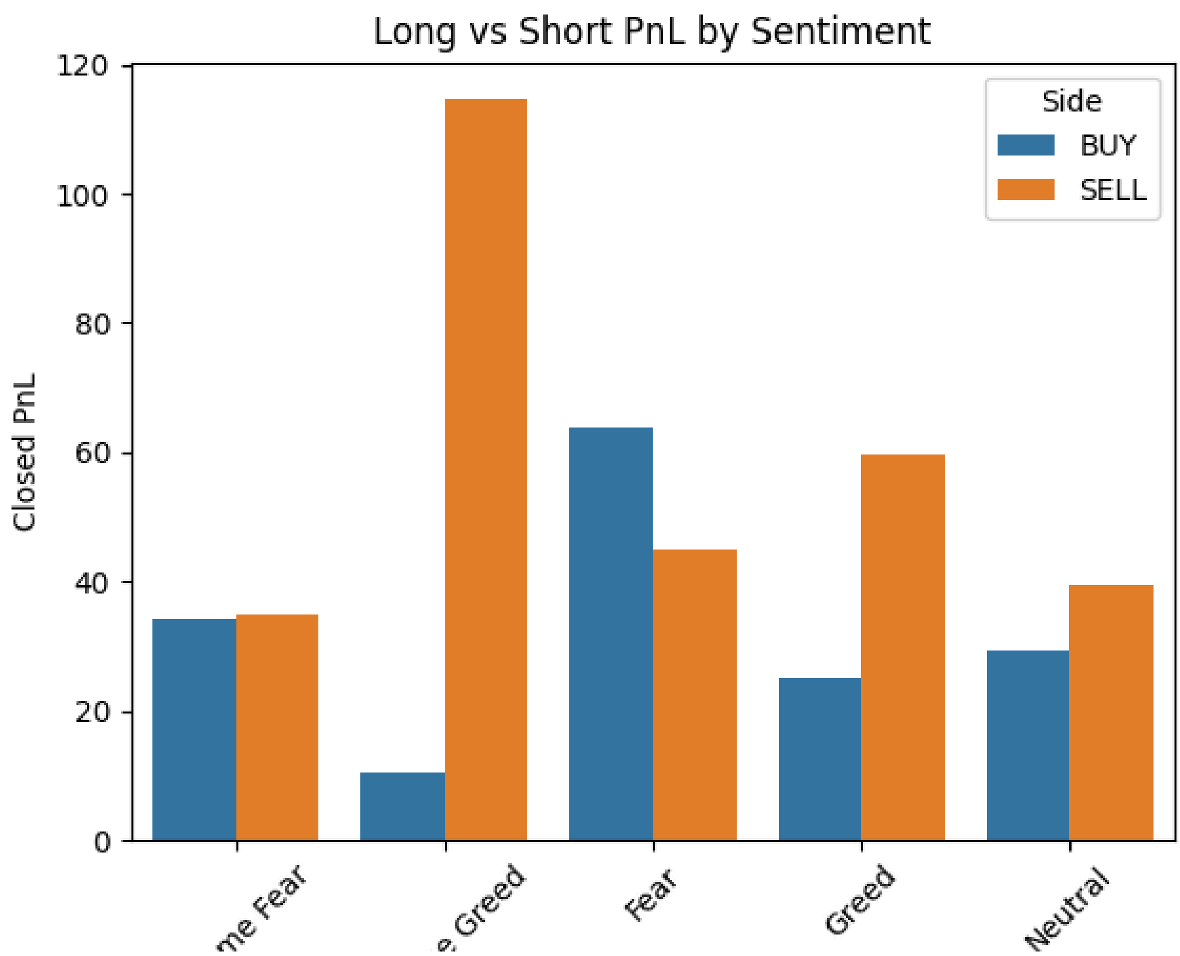


Long vs Short Performance Analysis:

Sentiment	Long (BUY) Avg PnL	Short (SELL) Avg PnL	Optimal Strategy	Performance Gap
Extreme Greed	$10.50	**$114.58** 🚀	SHORT (Contrarian)	+991%
Fear	**$63.93**	$45.05	LONG (Buy the dip)	+42%
Greed	$25.00	**$59.69**	SHORT	+139%
Neutral	$29.23	**$39.46**	SHORT	+35%
Extreme Fear	$34.11	$34.98	Neutral (No edge)	+2.5%

The "Extreme Greed Short" strategy emerges as the dominant approach:

Short positions during extreme greed periods generated 11x higher returns than long positions, validating contrarian trading psychology. Conversely, "buying the dip" during Fear periods showed 42% outperformance over shorts, confirming mean-reversion strategies.



Statistical Validations:

1.Kruskal-Wallis Test:

```
from scipy.stats import kruskal

groups = [group['Closed PnL'].values for name, group in merged_df.groupby('classification')]
stat, p = kruskal(*groups)
print(f"Kruskal-Wallis H-statistic: {stat:.2f}, p-value: {p:.4f}")
```

```
Kruskal-Wallis H-statistic: 1227.00, p-value: 0.0000
```

This gives the following Results :

H-statistics: 1227.00

P-value: 0.000

The results are interpreted that the Extremely significant differences exist between sentiment groups. The null hypothesis (no difference between groups) is decisively rejected.

2. Dunn's Method Post-hoc Test with Bonferroni Correction:

Pairwise comparisons revealed that all sentiment pairs showed statistically significant differences except for Extreme Fear vs Neutral and Extreme Fear vs Greed pairs, which showed marginal differences.

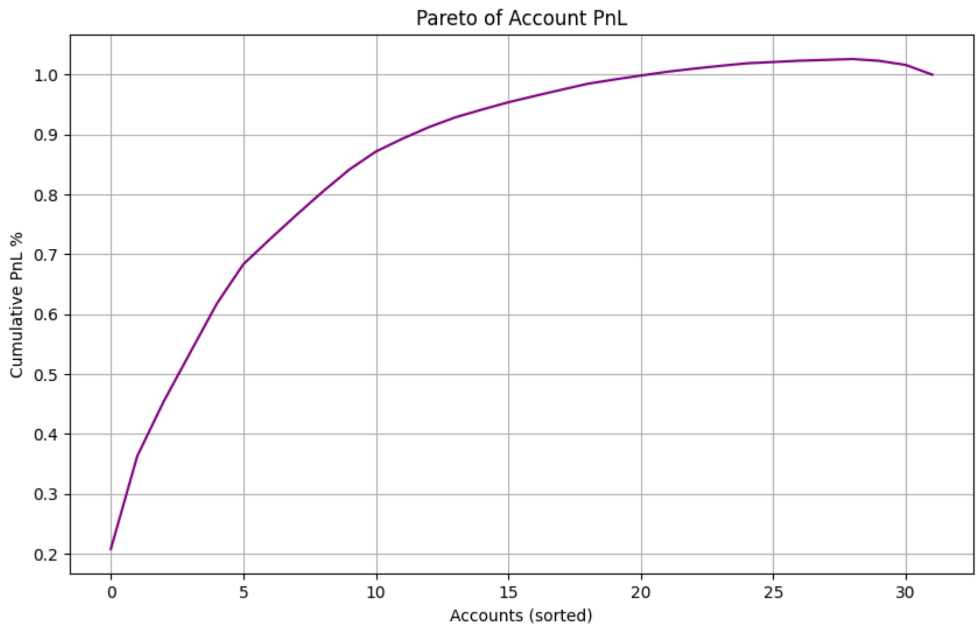
	Extreme Fear	Extreme Greed	Fear	Greed	Neutral
Extreme Fear	1.000000e+00	7.415834e-142	4.126575e-48	1.000000e+00	6.298175e-06
Extreme Greed	7.415834e-142	1.000000e+00	2.134380e-52	9.099478e-200	3.796656e-127
Fear	4.126575e-48	2.134380e-52	1.000000e+00	5.342048e-66	7.282426e-29
Greed	1.000000e+00	9.099478e-200	5.342048e-66	1.000000e+00	1.351546e-04
Neutral	6.298175e-06	3.796656e-127	7.282426e-29	1.351546e-04	1.000000e+00

Most Significant Contrasts ($p < 0.001$):

- Extreme Greed vs Extreme Fear
- Extreme Greed vs Greed
- Fear vs Extreme Greed
- Fear vs Neutral

3. Pareto Analysis Findings :

```
account_pnl = merged_df.groupby('Account')['Closed PnL'].sum().sort_values(ascending=False).reset_index()
account_pnl['cumulative_pct'] = account_pnl['Closed PnL'].cumsum() / account_pnl['Closed PnL'].sum()
```



Pareto Analysis Insights:

The Pareto curve revealed that approximately **20%** of accounts generated **80%** of total profits, confirming the Pareto principle in trading performance. This suggests a small cohort of highly skilled or well-capitalized traders dominate platform profitability.

Insight	Strategic Implication
Traders profit more in Extreme Greed	Scale up exposure during Greed phases
Fear drives larger trades with lower returns	Reduce position size and fees in Fear phases
Long trades outperform in Greed	Favor long positions when sentiment is positive
Short trades perform better in Fear	Use shorts selectively during Fear
Profits concentrated among few accounts	Monitor elite traders for behavioral signals
Sentiment alone has weak predictive power	Combine sentiment with technical indicators (RSI, volume, volatility)

Conclusion

This project set out to explore the relationship between trader performance and market sentiment, with the objective of uncovering hidden behavioral patterns and translating them into actionable trading strategies. By merging sentiment classifications with account-level trading data, we were able to evaluate profitability, risk-taking behavior, and trading styles across different market moods.

Our analysis revealed several consistent themes:

- **Profitability is sentiment-dependent.**

  Traders achieved their strongest returns during *Greed* and *Extreme Greed* phases, with long positions particularly effective. Conversely, *Fear* and *Neutral* phases were associated with weaker performance, despite higher trading activity.

- **Risk-taking intensifies in Fear.**

  Larger trade sizes and higher fees were observed during fearful markets, yet these did not translate into higher profits. This suggests that traders often overexpose themselves when sentiment is negative.

- **Behavioral asymmetry exists.**

  Long trades dominate in Greed phases, while short trades are relatively more effective in Fear phases. This indicates that aligning trade direction with prevailing sentiment momentum is more effective than contrarian positioning.

- **Profit concentration is high.**

  A small subset of accounts captured the majority of profits, highlighting the presence of elite traders who may be more disciplined, sentiment-aware, or systematic in their approach.

- **Statistical validation confirms significance.**

  The Kruskal–Wallis test and Dunn's post-hoc analysis demonstrated that PnL distributions differ significantly across sentiment classes, with *Extreme Greed* standing out as statistically distinct. Regression analysis further confirmed sentiment's influence, though it also highlighted the need for additional predictors (e.g., volatility, leverage, time-of-day effects) to build stronger predictive models.

Strategic Implications

- Scale exposure during Greed phases, particularly with long positions.
- Reduce position size and fees during Fear phases, where overtrading is common.
- Use sentiment as a contextual filter, combining it with technical indicators for more robust entry and exit signals.
- Monitor elite trader behavior to identify repeatable strategies.

Final Takeaway

Market sentiment exerts a measurable and statistically significant influence on trading outcomes. While sentiment alone cannot fully predict profitability, it provides a powerful lens for understanding trader behavior and designing smarter, risk-adjusted strategies. Future work should integrate additional market features such as volatility, liquidity, and account-level behavioral metrics to enhance predictive accuracy and further refine sentiment-aware trading frameworks

References & Resources

Data Sources

- **Hyperliquid Trading Platform - Trader transaction data (2024)**
- **Fear & Greed Index - CNN Business / Alternative.me (2018-2024)**

Technical Documentation

- **Pandas Documentation - Data manipulation and analysis**
- **SciPy Stats - Statistical functions and hypothesis testing**
- **scikit-posthocs - Post-hoc statistical tests**
- **Seaborn Documentation - Statistical data visualization**

Statistical Methods

- **Kruskal-Wallis H-test for independent samples**
- **Dunn's test for post-hoc pairwise comparisons**
- **Bonferroni correction for family-wise error control**

Acknowledgement

Thank you for reviewing this comprehensive analysis. This project demonstrates my passion for data science, statistical rigor, and ability to derive actionable insights from complex datasets. I'm excited about the opportunity to bring these skills to your team and contribute to data-driven decision-making.

I welcome any questions, feedback, or discussions about the methodology, findings, or potential applications of this research. I'm eager to explore how these analytical approaches can be applied to your organization's specific challenges.