Relationship Between
Trader Behavior & Market Sentiment

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Summary:

Analyze the relationship between trader behavior - profitability, risk, volume, and leverage and market sentiment (Fear vs Greed).
The goal is to identify patterns and divergences to understand how trading behavior aligns or diverges from market emotions, enabling smarter, sentiment-aware trading strategies.

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1. Data Overview

Dataset	Description	Key Fields
Bitcoin Market Sentiment (fear_greed.csv)	Fear–Greed Index for Bitcoin markets	Date,Timestamp, Classification
Hyperliquid Trader Data (historical.csv)	Account-level trading logs, orders, leverage, PnL	account, execution_price, size, side, time, closedPnL, etc

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2. Data Preparation

Steps performed:

1. Cleaned and standardized column names.
2. Parsed mixed date/time formats (IST timestamps and UNIX).
3. Computed:
   - notional = size_tokens × execution_price
   - is_profitable = closed_pnl > 0
4. Converted all timestamps into a unified date field.
5. Merged daily sentiment labels (Fear / Greed) into the trade dataset.

Key intermediate files:

- processed_traders.csv
- trades_with_sentiment.csv
- daily_aggregates.csv

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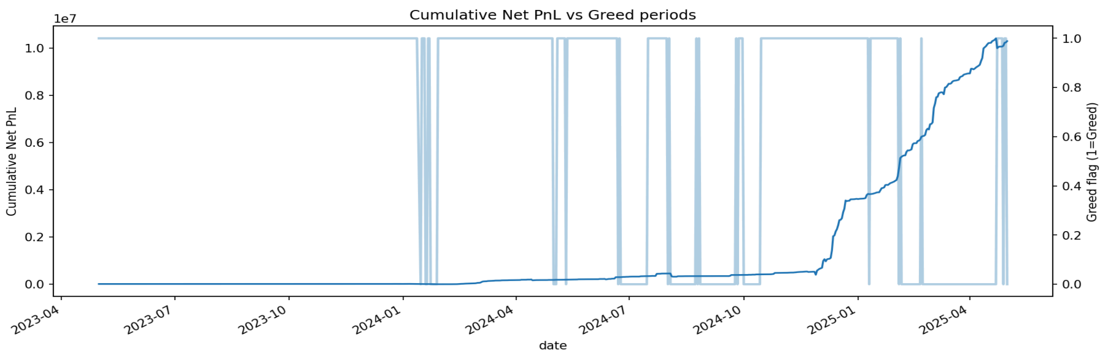
3. Exploratory Data Analysis (EDA)

4.1 Daily Trading Trends

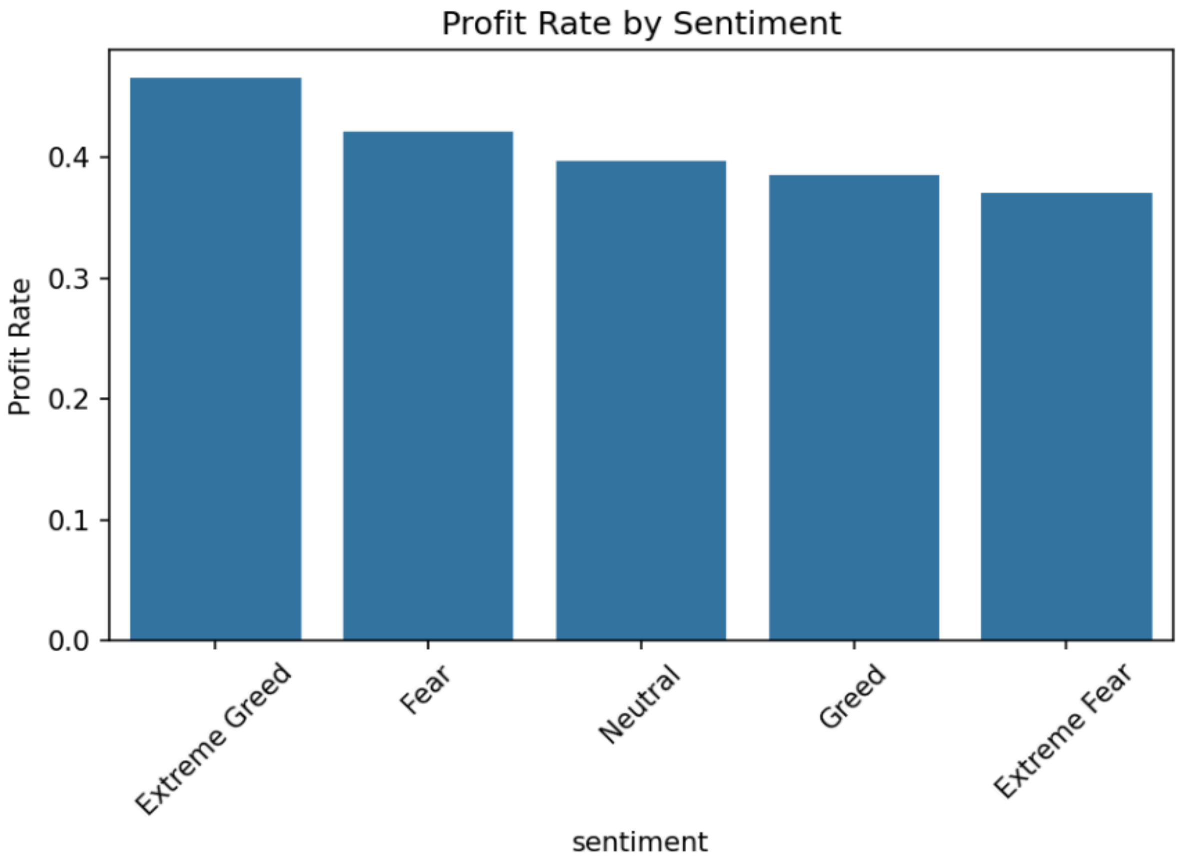
- Aggregated **daily metrics**:
  net_pnl, total_volume, profit_rate, trade_count, and sentiment.
- Observed that **trading activity spikes during Greed phases**, reflecting higher participation and risk-taking.



Line Plot — Cumulative Net PnL vs Greed Periods]
File: outputs/cumulative_pnl_vs_greed.png

4.2 Profitability Across Sentiment

- Average **profit rate** during Greed periods was slightly higher but **statistically insignificant** (p ≈ 0.10).
- Traders showed **cautious behavior in Fear phases**, reducing volume but limiting losses.



Bar Plot — Profit Rate by Sentiment]
File: outputs/profit_rate_by_sentiment.png

4.3 Distribution Analysis

- Mann–Whitney U Test comparing Fear vs Greed profit distributions:
  Statistic = 1.98×10^8, p = 0.1062
  → No strong statistical evidence that profit levels differ significantly by sentiment.

5. Predictive Modeling

Goal: Predict whether a trader's day is profitable using behavioral and sentiment features.

Model	Features	AUC	Accuracy
Random Forest Classifier	trades, total_volume, sentiment_greed	**0.66**	**0.68**

- Precision (profitable): **0.69**
- Recall (profitable): **0.88**

Interpretation:
Sentiment slightly improves predictability, but **behavioral features dominate** model performance.

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6. Insights

Category	Observation
Market Sentiment	Greed periods show higher trade volume and leverage but inconsistent profits.
Trader Behavior	Fear periods involve lower risk exposure and fewer losses.
Profitability Drivers	Consistent traders perform better independent of sentiment; impulsive trades rise during Greed.
Risk Patterns	Leverage tends to increase in high-sentiment periods, amplifying PnL volatility.

7. Recommendations

1. **Integrate Real-Time Sentiment Feeds**
   → Use APIs to adapt leverage dynamically as sentiment shifts.

2. **Leverage Control Rules**
   → Reduce exposure when the sentiment index exceeds “Extreme Greed.”

3. **Behavior Clustering**
   → Cluster accounts by trading style to detect overconfident traders in Greed cycles.

4. **Cross-Asset Validation**
   → Apply model to other crypto assets to validate sentiment consistency.

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8. Deliverables

Category	Files Produced
Data	processed_traders.csv, trades_with_sentiment.csv, daily_aggregates.csv, account_daily_aggregates.csv
Visuals	cumulative_pnl_vs_greed.png, profit_rate_by_sentiment.png
Notebook	notebook_1.ipynb
Report	ds_report.pdf (this document)

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9. Conclusion

The analysis demonstrates that **market sentiment influences trader behavior but not direct profitability**.
Greed phases drive **higher activity and leverage**, while Fear phases promote **risk aversion**.

Although statistical tests show no significant profit difference, sentiment still acts as a **contextual signal** guiding volume and risk exposure.

This project establishes a foundation for **sentiment-driven trade optimization**, integrating behavioral analytics into algorithmic decision-making frameworks.

End of Report

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