Trader Performance vs Market Sentiment – Analysis Report

1. Objective

This analysis examines how **market sentiment**, measured by the Crypto Fear & Greed Index, influences **trader behavior and performance** on the Hyperliquid exchange. The goal is to identify patterns that can inform future risk management and strategy design.

2. Data Sources

1. **Hyperliquid Trade Data**
   - Columns: account, symbol, execution_price, size, side, time, closedPnL, leverage, fee, etc.
   - Each row represents a single trade execution.
2. **Crypto Fear & Greed Index**
   - Columns: date, classification (Extreme Fear, Fear, Neutral, Greed, Extreme Greed).
   - Classifications are derived from a 0–100 sentiment score.

The datasets were merged by trade date so that each trade record includes the prevailing market sentiment.

3. Data Preparation

- **Timestamp alignment:** Converted execution times to date format (YYYY-MM-DD).
- **Merging:** Joined sentiment data to each trade.
- **Feature engineering:**
  - is_profitable: Boolean, ClosedPnL > 0.
  - norm_pnl: ClosedPnL normalized by trade size.
  - fee_pct: Fee as a percentage of trade size.
  - classification_grouped: Sentiment grouped into Fear, Neutral, Greed.
  - Computed cumulative PnL and maximum drawdowns per account.

4. Exploratory Data Analysis (EDA)

4.1 Sentiment Distribution

- Trading activity was higher on **Greed** days (~90k trades) than on **Fear** (~83k) or **Neutral** (~38k) days.

4.2 Profitability vs. Sentiment

Sentiment	Win Rate (%)	Avg. Normalized Return
Greed	~42.0	2.87%
Fear	~40.8	1.26%
Neutral	~39.7	0.99%

- Traders achieved **higher win rates and returns in Greed periods**.
- Extreme Greed days showed ~46.5% profitable trades, while Extreme Fear days dropped to ~37.1%.

4.3 Return Characteristics

- Median normalized PnL = **0.0** → Most trades were breakeven or very small in impact.
- Distribution is highly skewed:
  - Maximum single-trade gain: ~+340%.
  - Maximum single-trade loss: ~–38,400% (likely extreme leverage).

4.4 Fee Analysis

- Mean fee percentage: ~0.035%.
- Trading costs were negligible relative to profits/losses.

4.5 Risk – Drawdowns

- Maximum cumulative drawdown:
  - Greed: –$479k
  - Fear: –$166k
  - Neutral: –$133k

- While Greed periods produced the highest profits, they also carried **larger risk swings**.

5. Key Insights

- **Market sentiment impacts outcomes:** Greed phases correlate with higher win rates and higher average profits.
- **Fear phases see larger trade sizes:** Traders tended to take bigger positions when the market was fearful.
- **Risk increases in bullish markets:** Larger potential gains are paired with deeper drawdowns during Greed periods.
- **Fees are not a significant factor** in performance.
- **Performance gap widens by skill:** Strong traders excel in Greed conditions, while weaker traders often lose.

6. Extended Analysis – Predictive Modeling

A simple machine learning exercise tested whether trade outcomes (is_profitable) could be predicted using trade features and sentiment:

Model	Accuracy	F1 Score
Random Forest	**99.4%**	**99.4%**
XGBoost	97.6%	97.6%
MLP Neural Net	30.3%	15.3%

- **Best performing model:** Random Forest.
- Top predictive features included: trade size, sentiment classification, and account-level statistics.

7. Project Files

Due to size constraints:

- Original datasets are not included in this repository. Download links are provided separately.

- Processed CSVs and trained model files can be reproduced by running the Jupyter Notebook.

8. Tools Used

- Python (Pandas, NumPy, Matplotlib, Seaborn)
- Scikit-learn, XGBoost
- Jupyter Notebook

9. Next Steps

- Incorporate leverage, long/short bias, and time-of-day effects into analysis.
- Build dashboards for real-time monitoring of trader performance by sentiment.