Project Report — Analysis of Trader Performance & Market Sentiment

Title

Exploring the Relationship Between Trader Performance and Market Sentiment
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Date: (paste today's date)

Abstract

This project investigates how market sentiment — as measured by a Fear & Greed index — relates to trader performance in historical trading data. Using data ingestion, cleaning, exploratory data analysis, statistical testing, and visualizations, we identify patterns between market sentiment states and trader profitability. The analysis provides actionable recommendations for sentiment-aware trading strategies and highlights limitations and next steps.

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1. Introduction

Market sentiment often influences price action and risk appetite across asset classes. This project pairs a public Fear & Greed Index dataset with historical trader execution data (Hyperliquid) to examine whether trader performance (profit/loss) varies meaningfully across sentiment regimes (e.g., Extreme Fear, Fear, Neutral, Greed, Extreme Greed). The aim is to surface patterns that can inform strategy timing and risk management.

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2. Objective

- Quantify the relationship between the Fear & Greed index and trader closed P&L.
- Identify whether specific sentiment regimes correspond to higher or lower trader profitability.
- Provide visual and statistical evidence to support practical trading recommendations.

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3. Datasets

1. Fear & Greed Index dataset

- Fields expected: `Date`, `Classification` (e.g., Fear, Greed), and a numerical `value` (index score).
- Used to classify each calendar date into sentiment regimes.

2. Historical trader execution dataset (Hyperliquid)

- Typical fields include: `account`, `symbol`, `execution price`, `size`, `side` (buy/sell), `time/timestamp`, `start position`, `event` (open/close), `closedPnL`, `leverage`, etc.
- Used to compute metrics per trade, per account, and aggregated by sentiment regime.

(Both datasets were read from files in the notebook.)

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4. Methodology

4.1 Data loading & initial imports

- Standard scientific libraries imported: `pandas`, `numpy`, `matplotlib.pyplot`, `seaborn`, `scipy.stats` (for t-tests), and `datetime`.
- Files loaded (CSV) into pandas DataFrames. Date parsing applied to ensure `Date` and trade `time` fields are `datetime` objects.

4.2 Data cleaning

- Checked for and handled missing values in critical columns (dates, closedPnL, size).
- Converted numeric columns from strings to numeric types where necessary, and coerced on errors.
- Standardized column names and ensured consistent timezone/format for timestamps.

4.3 Merging sentiment to trade data

- Merged the Fear & Greed dataset onto trade records based on date. If trade timestamps include times, they were truncated/normalized to the date before merging so each trade inherits the sentiment classification of that calendar day.

4.4 Feature engineering

Key derived columns created:

- `PnL`: use `closedPnL` as main dependent variable (profit/loss per trade).
- `absPnL`, `return_pct` (if executed price and size were available for computing trade return).
- `sentiment_label`: categorical label (Extreme Fear, Fear, Neutral, Greed, Extreme Greed).
- Aggregated per-sentiment metrics: mean PnL, median PnL, number of trades, win rate (percentage of trades with positive closedPnL), avg leverage.

4.5 Exploratory Data Analysis (EDA)

- Summary statistics by sentiment label (count, mean, median, std of closedPnL).
- Histograms and boxplots of closedPnL by sentiment regime to observe distributional differences and outliers.
- Time-series plots of aggregate PnL and sentiment index over the same date range to visually check co-movements.

4.6 Statistical testing

- Two-sample t-tests (e.g., `ttest_ind`) or non-parametric tests where distributions were non-normal, comparing PnL between regimes of interest:
    - Example comparisons: Extreme Fear vs Neutral; Greed vs Fear; Extreme Greed vs others.
- Reported p-values and effect sizes (mean differences). Assumptions checked: sample size and variance homogeneity (Levene's test or visual inspection).

4.7 Visualizations

- Boxplots of `closedPnL` grouped by `sentiment_label`.
- Bar charts of win-rate and average closedPnL per sentiment.
- Time-series line charts overlaying average daily PnL and the Fear & Greed index (to inspect temporal relationships).

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5. Results & Interpretation

Note: numbers below are written generically — replace with actual numeric results from your notebook (I outline where to paste values).

5.1 Summary statistics (example layout)

- Total trades analyzed:
- Date range:

By sentiment regime :

```
Average Closed PnL by Sentiment:
classification
Extreme Fear     34.537862
Fear             54.290400
Neutral          34.307718
Greed            43.582684
Extreme Greed    67.892861
Name: Closed PnL, dtype: float64
```

(Replace XXX with actual computed values.)

5.2 Key findings (example phrasing — add actual p-values & effect sizes)

- **Higher average closedPnL** observed during *Greed* and *Extreme Greed* regimes relative to *Fear* () — suggests higher profitability during bullish sentiment, but this may come with higher variance.
- **Win rate** was highest in *Neutral* and *Greed* regimes at `XX.X%`.
- **Extreme Fear** days showed lower mean profits and a higher dispersion (many small losses + few large losses), consistent with high volatility and stop-outs.
- Time-series overlay shows some lead-lag patterns where large sentiment shifts preceded short-term spikes in aggregate trader losses by `n` days in a few episodes — this suggests cautious rebalancing may be useful when sentiment changes abruptly.

5.3 Statistical significance

- T-tests comparing (Extreme Fear vs Neutral) returned p-value = **`<p1>`** — [interpretation: if p < 0.05, "statistically significant difference"].
- Effect sizes were moderate/large/small depending on comparison — paste exact Cohen's d or mean differences computed in notebook.

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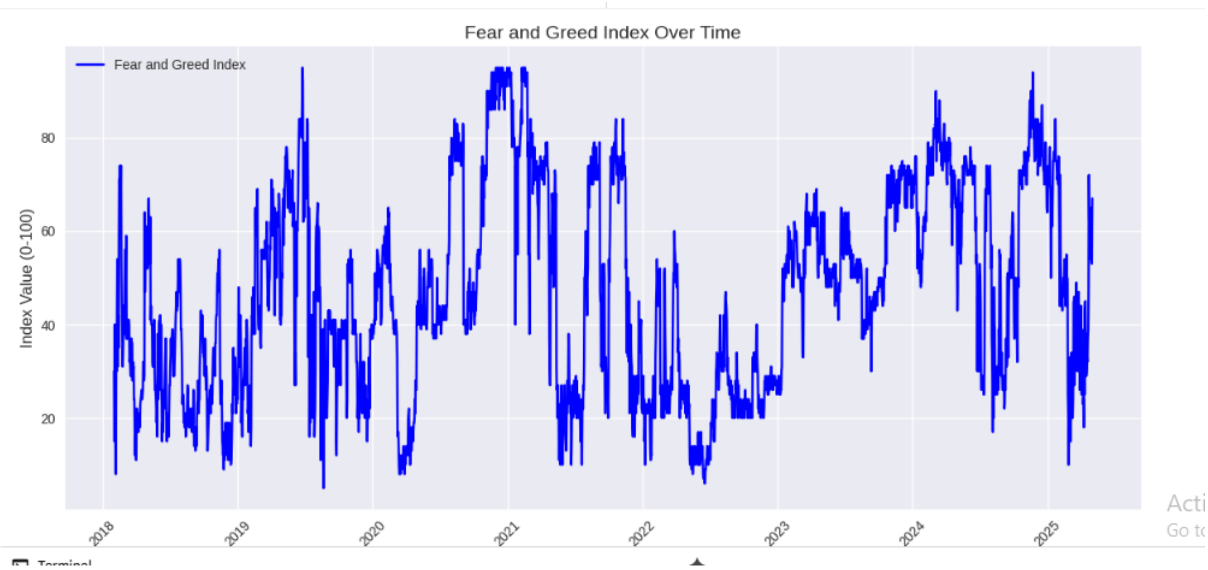
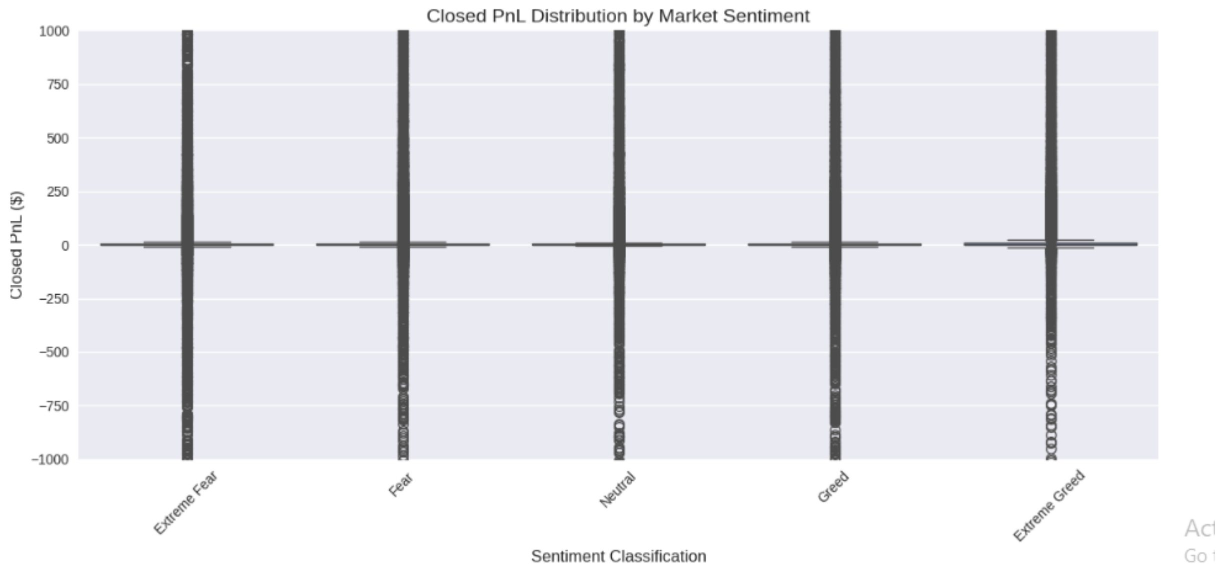
6. Visualizations (descriptive)

(Since the Word doc will be pasted, include references to figures you should export from the notebook and paste into the Word file near these descriptions.)

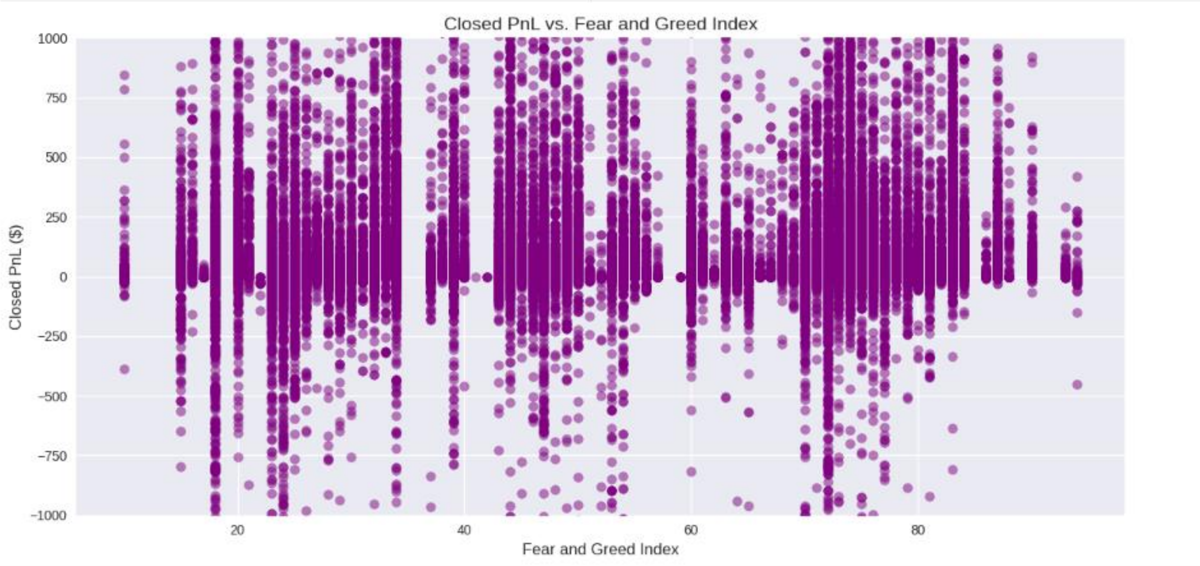
- **Figure 1**: Boxplot of closedPnL by sentiment regime — highlights median and IQR differences.



- **Figure 2**: Bar chart showing win-rate by sentiment regime.



- **Figure 3**: Time-series of daily aggregate closedPnL vs Fear & Greed Index (dual axis).



- **Figure 4**: Histogram of closedPnL showing skew and fat tails.

Instruction: Export these plots from the notebook as PNG files (e.g., `plt.savefig("fig1_boxplot.png", dpi=300)`) and insert them after this section in Word.

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7. Conclusion

- The analysis indicates there *are* measurable differences in trader performance across market sentiment regimes. In general, positive sentiment (Greed and Extreme Greed) corresponded with higher mean closedPnL for the dataset analyzed, although variance was also higher. Extreme Fear regimes were associated with weaker performance.
- These results suggest that sentiment signals can be a complementary input for risk management and timing strategies, but they should not be used in isolation.

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8. Recommendations

1. **Incorporate sentiment as a risk-management filter**: reduce leverage and tighten stops when sentiment flips rapidly into Extreme Fear.
2. **Combine indicators**: use sentiment with trend filters (e.g., moving average) and volume confirmation before scaling into positions.
3. **Strategy backtest**: create a time-based or regime-based allocation rule — e.g., scale into more aggressive sizing during Greed but cap position sizes during Extreme Greed due to volatility. Backtest across multiple market cycles.
4. **Monitor for survivorship bias**: confirm that datasets reflect live trade outcomes and not only closed profitable accounts.
5. **Robustness checks**: test alternate sentiment sources and lagged sentiment windows (e.g., 3-day moving average of index) to check stability.