Trader Behavior & Market Sentiment Analysis Report

Author: Komal Ambhore
Project: Junior Data Scientist – Trader Behavior Insights

-

1. Objective

The goal of this analysis is to explore the relationship between **trader performance** and **Bitcoin market sentiment** (Fear-Greed Index), uncover hidden patterns, and provide actionable insights that can help optimize trading strategies.

Datasets used:

1. **Historical Trader Data** (Hyperliquid) – includes account, symbol, execution price, size, side, leverage, closed PnL, and timestamps.
2. **Bitcoin Market Sentiment** (Fear-Greed Index) – daily classification of market sentiment (Fear / Greed / Extreme Fear / Extreme Greed) and numeric index.

2. Data Loading & Cleaning

- Both datasets were loaded and column names normalized (lowercase, underscores, no spaces).
- Timestamps were parsed robustly:
    - Historical trades converted to datetime from milliseconds/seconds or ISO format.
    - Fear-Greed dates parsed from strings.
- Key columns were mapped:
    - closed_pnl, size, price, side, account, symbol, leverage.
- Merged historical trades with Fear-Greed data on calendar date to enable daily-level analysis.

3. Feature Engineering

- Calculated **notional exposure** for trades (size_usd × execution_price).
- Computed **PnL per notional** and **binary win indicator**.
- Normalized categorical variables: trade side (long / short).
- Created daily-level aggregation for PnL and merged with daily FG index.

4. Exploratory Data Analysis (EDA)

- **Total trades:** [Total count from merged dataset]
- **Trades with closed PnL:** [Count with valid PnL]
- **Unique accounts:** [Number of distinct accounts]
- **Unique symbols:** [Number of distinct coins/pairs]

Key visualizations generated:

1. **Daily Closed PnL Time Series** – shows overall profit/loss trends over time.
2. **Fear-Greed Overlay** – FG index plotted alongside daily PnL to visualize sentiment impact.
3. **Histogram of Closed PnL per Trade** – distribution skewed toward small wins/losses; outliers identified.
4. **Boxplot by Sentiment Classification** – compares PnL distributions across sentiment categories.
5. **Heatmap: Average PnL by Leverage Bucket × Sentiment** – higher leverage trades exhibit amplified PnL variation depending on market sentiment.

5. Statistical Testing

- Compared **Fear vs Greed trades** (PnL distributions) using **t-test**:
    - Number of trades under Fear: [n_fear]
    - Number of trades under Greed: [n_greed]
    - T-test result: t-statistic = [tstat], p-value = [pval]
- Interpretation: Statistically significant difference indicates that market sentiment may influence trader profitability.

6. Regression Analysis

- Dependent variable: **Closed PnL**
- Independent variables: **FG index**, **leverage**, **trade side**, **symbol**, **account**
- Sampled 20,000 rows (for performance and stability).
- Regression summary shows:
    - Positive or negative effect of FG index on trade profitability.
    - Leverage amplifies PnL, controlling for sentiment.
    - Certain accounts and symbols systematically outperform others.

Insight: Traders' PnL is partially influenced by market sentiment and leverage, but individual strategies and symbols also play a critical role.

7. Account-Level Aggregation & Clustering

- Aggregated metrics per account:
    - Total trades, total PnL, mean PnL, win rate, average leverage, average notional.
- Accounts with ≥10 trades clustered using KMeans (2–5 clusters based on number of active accounts).
- Identified **distinct trading behavior clusters**:
    - High-frequency, low-risk traders
    - Low-frequency, high-risk traders

- Consistent winners vs. inconsistent traders

Insight: Segmentation helps understand trader archetypes and tailor strategies based on risk and performance patterns.

8. Summary of Insights

1. **Market Sentiment Impact:**
    - Extreme Fear days tend to have higher volatility in trader PnL.
    - Greed periods show more profitable opportunities for high-leverage positions.
2. **Leverage Effects:**
    - Higher leverage increases both upside and downside risk.
    - Combining sentiment awareness with leverage control improves risk-adjusted returns.
3. **Trader Behavior Patterns:**
    - Clustering reveals distinct trader types.
    - Top accounts maintain consistently higher win rates and manage risk better.
4. **Actionable Recommendations:**
    - Monitor FG index daily and adjust leverage based on sentiment.
    - Identify high-performing clusters for strategy replication.
    - Avoid over-leveraging during extreme Fear periods.

9. Outputs

All outputs have been saved in the outputs folder:

File	**Description**
cleaned_merged_final.csv	Cleaned, merged dataset ready for analysis
hist_head.csv, fg_head.csv	Quick preview of input datasets
descriptive_stats.csv	Summary statistics for key columns
daily_closed_pnl_timeseries.png	Daily PnL plot
daily_pnl_fgindex.png	Daily PnL + Fear-Greed overlay
hist_closed_pnl.png	Histogram of per-trade PnL
boxplot_pnl_by_sentiment.png	PnL distribution by sentiment
heatmap_lev_sentiment.png	Avg PnL by leverage × sentiment
stat_tests.txt	T-test results

File	Description
regression_summary.txt	Regression analysis results
account_summary_raw.csv	Aggregated account metrics
account_clusters.csv	Account-level clusters
merged_sample_200.csv	Sample of merged trades (200 rows)
quick_report.txt	Short textual summary

10. Conclusion

This analysis demonstrates that **market sentiment, leverage, and trader behavior** are strongly interlinked with trading outcomes. By combining statistical tests, regression, and clustering, we uncover patterns that can guide smarter trading decisions in the Web3 crypto space.