Bitcoin Market Sentiment vs Trader Performance Analysis

Primetrade.ai — Data Science Internship · Round 0

> Analysing how Bitcoin Fear/Greed Index sentiment (2018–2025) relates to trader behavior and performance on Hyperliquid, using 211,224 trade fills from 32 unique accounts.

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Project Overview

Question: Does Bitcoin market sentiment (Fear vs Greed) meaningfully predict or correlate with how traders perform on Hyperliquid?

Short answer: Not in a straightforward way. The analysis reveals a more nuanced story — sentiment shapes *how* traders behave (sizing, directionality, activity), but the link to *outcomes* is weaker than expected and not statistically significant for most metrics. The real performance differentiator is trader segment, not sentiment.

Tech stack: Python · pandas · scikit-learn · scipy · seaborn/matplotlib · Google Colab

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Datasets

File	Rows	Period	Key Columns
`fear_greed_index.csv`	2,645	Feb 2018 – May 2025	`date`, `value` (0–100), `classification`

File	Rows	Period	Key Columns
`historical_data.csv`	211,224	Dec 2024	`Account`, `Closed PnL`, `Size USD`, `Side`, `Direction`, `Timestamp IST`

Sentiment Class Distribution (full history)

Class	Days	Score Range
Extreme Fear	~550	0–24
Fear	~780	25–44
Neutral	~430	45–54
Greed	~580	55–74
Extreme Greed	~305	75–100

Critical Data Note — Open vs Close Fills

On Hyperliquid, every position has two fills: one when it **opens** (`Closed PnL = 0`) and one when it **closes** (`Closed PnL ≠ 0`). Analysing all fills naively would corrupt PnL metrics with thousands of zeros. This pipeline separates them:

- **All fills** → used for volume, frequency, and fee metrics
- **Closed fills only** → used for PnL, win rate, and risk metrics

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Setup & Usage

1. Open in Google Colab

Upload `untitled33.py` as a notebook or paste into a new Colab cell.

2. Upload data files

```
/content/fear_greed_index.csv
/content/historical_data.csv
```

3. Run all cells top to bottom

Outputs are saved to `/content/outputs/` and auto-downloaded as a zip at the end.

Dependencies (auto-installed)

```
pandas  numpy  matplotlib  seaborn  scipy  scikit-learn
```

Methodology

Data Pipeline

```
Raw CSVs
  ↓
Quality checks (missing values, duplicates, type casting)
  ↓
Separate OPEN fills from CLOSE fills (Direction column)
  ↓
Clip Closed PnL outliers at 1st–99th percentile
  ↓
Parse Timestamp IST (DD-MM-YYYY HH:MM, dayfirst=True)
  ↓
Map 5 sentiment classes → binary (Fear / Neutral / Greed)
  ↓
Left-merge on date_only
  ↓
Daily per-account aggregation (two tables: all fills + closed fills)
  ↓
Analysis → Segmentation → Model
```

Sentiment Mapping

Raw Classification	Binary Label	Binary for Stats Tests
Extreme Fear	Fear	Fear
Fear	Fear	Fear
Neutral	Neutral	*(excluded from Fear vs Greed t-tests)*
Greed	Greed	Greed
Extreme Greed	Greed	Greed

Daily Metrics Computed

Metric	Source	Description
`num_closed_trades`	Closed fills	Trade count per account per day
`total_pnl`	Closed fills	Gross realised PnL
`net_pnl`	Closed fills - fees	PnL after trading fees
`win_rate`	Closed fills	Fraction of profitable closes
`avg_trade_size_usd`	Closed fills	Average notional per trade
`drawdown_proxy`	Closed fills	Intraday PnL standard deviation
`long_pct_closed`	Closed fills	Fraction of long-side closes
`total_fees`	All fills	Sum of fees paid

Key Findings

Finding 1 — Sentiment Has No Statistically Significant Effect on Performance

The Mann-Whitney U test (two-sided, $\alpha = 0.05$) found **no significant difference** between Fear and Greed days for any tested metric.

Metric	Fear Mean	Greed Mean	Δ	p-value	Significant?
Daily PnL ($)	~$5,100	~$4,200	−$900	0.1004	❌ No
Win Rate	~84%	~85%	+1%	0.2478	❌ No
Closed Trades/Day	—	—	—	0.4514	❌ No
PnL Std Dev	—	—	—	0.4586	❌ No
Avg Trade Size (USD)	—	—	—	0.2223	❌ No
Net PnL after Fees	—	—	—	0.0747	❌ No

> **Interpretation:** This is a meaningful result in itself — it means traders in this dataset cannot rely on sentiment as a reliable signal for *when* to trade. Other factors dominate performance variance.

Finding 2 — Trade Size and Activity Decrease Monotonically from Fear → Greed

The behavior heatmap reveals a clear structural pattern across all 5 sentiment classes:

Metric	Extreme Fear	Fear	Neutral	Greed	Extreme Greed
Avg Closed Trades/Day	**81.94**	67.00	65.83	56.28	52.68
Avg Trade Size (USD)	**$13,233**	$11,126	$8,576	$7,196	$6,401
Win Rate	0.77	0.86	0.83	0.85	**0.87**
Total PnL ($)	4,673	**5,332**	4,016	3,789	4,620
Total Fees ($)	**178.78**	194.14	137.69	120.47	60.62

Traders are **most active and deploy the largest sizes on Fear days** — the opposite of conventional wisdom. During Extreme Greed, activity and sizing drop significantly. This could indicate professionals fading rallies and accumulating on fear, while retail sentiment drives the headline index.

Finding 3 — Trade Size Is Negatively Correlated with FG Score (Statistically Significant)

Continuous correlation analysis with the numeric Fear/Greed score (0–100):

Metric	Pearson r	p-value	Interpretation
Daily PnL	−0.006	0.8006	No relationship
Win Rate	+0.044	0.0683	Marginal positive trend
Avg Trade Size (USD)	**−0.080**	**0.0010**	Significant: larger trades on Fear days

The only statistically significant continuous relationship is trade size declining as sentiment becomes more greedy — reinforcing Finding 2.

Finding 4 — Traders Are Short-Biased Across All Sentiment Classes

Long trade fraction never exceeds 50% in any sentiment class:

Sentiment	Long %
Extreme Fear	34.9%
Fear	40.1%
Neutral	37.6%
Greed	**40.9%** ← peak
Extreme Greed	36.1%

The community skews short throughout — suggesting systematic short strategies or hedging dominates this account set. The conventional "greed = long" narrative is not reflected here.

Finding 5 — Neutral Days Sit Closer to Fear in Activity, Closer to Greed in Size

Neutral days show mid-range trade counts (65.83) and mid-range trade sizes ($8,576), sitting between the Fear and Greed extremes on most metrics. They should not be treated as a default "normal" — they inherit slightly elevated risk (fees: $137.69) without a corresponding uplift in returns.

Trader Segmentation

32 Unique Accounts — 4-Quadrant Rule-Based Segmentation

Segmented on median splits of: **avg daily trades** (frequency) and **lifetime PnL** (profitability).

Segment	Traders	Avg Daily Trades	Lifetime PnL	Avg Win Rate	Fee Drag
Frequent / Profitable	**10**	High	High	~83%	Low
Frequent / Loss-Making	6	High	Low	~84%	**Very High**
Infrequent / Profitable	6	Low	High	~87%	Low
Infrequent / Loss-Making	**10**	Low	Low	~80%	Low

Key observation: Win rates are remarkably similar across all 4 segments (80–87%). The performance gap is driven by **fee drag**, not skill. The Frequent/Loss-Making segment has a wide, variable fee drag (up to 45% of |PnL|), confirming that overtrading erodes a viable edge.

The top traders by lifetime PnL (Infrequent/Profitable, Frequent/Profitable) achieved $400k–$900k+ in lifetime PnL.

K-Means Clustering (k=3)

Three behavioral archetypes identified via unsupervised clustering on scaled features:

Cluster	n	Profile
Cluster 0	9	Mid-frequency, moderate win rate (~83–91%)
Cluster 1	7	Low-to-mid frequency, highest variability in win rate
Cluster 2	16	Largest group; wide range of trade frequencies (10–440/day)

Predictive Model

Task: Predict whether a trader will have a profitable day tomorrow, given today's behavior and sentiment.

Target: `next_day_profitable` (binary: tomorrow's PnL > 0)

Features

- `lag1_total_pnl` — previous day's gross PnL
- `lag1_drawdown_proxy` — previous day's risk (PnL std dev)
- `lag1_avg_trade_size_usd` — previous day's avg trade size
- `lag1_total_fees` — previous day's fee spend
- `lag1_num_closed_trades` — previous day's trade count
- `fg_score_lag1` — previous day's Fear/Greed score (0–100)
- `lag1_win_rate` — previous day's win rate
- `lag1_long_pct_closed` — previous day's long bias
- `sentiment_today_enc` — today's sentiment (0=Fear, 1=Neutral, 2=Greed)

Results

Model	Test Accuracy	ROC-AUC	CV-AUC
Logistic Regression	—	—	—
Random Forest	**Best**	**Best**	—

Model	Test Accuracy	ROC-AUC	CV-AUC
Gradient Boosting	—	—	—

Best model: Random Forest

Feature Importance (Random Forest)

The model confirms what the exploratory analysis found — **sentiment is a minor predictor**:

1. `lag1_total_pnl` ← **most important** (yesterday's PnL predicts tomorrow's)
2. `lag1_drawdown_proxy` (risk proxy)
3. `lag1_avg_trade_size_usd` (position sizing)
4. `lag1_total_fees` (fee activity)
5. `lag1_num_closed_trades` (trade count)
6. `fg_score_lag1` (Fear/Greed score)
7. `lag1_win_rate`
8. `lag1_long_pct_closed`
9. `sentiment_today_enc` ← **least important**

> ⚠️ **Model caveat:** The dataset is highly imbalanced — profit days dominate. The confusion matrix shows the model predicts "Profit Day" for nearly all cases (272 correct, 42 false positives, 0 true negatives). This suggests the model has learned the base rate, not a true signal. A larger, more balanced dataset would be needed for a production-grade classifier.

Strategy Recommendations

Strategy 1 — Sentiment-Responsive Risk & Fee Management

Evidence: Trade size is significantly larger on Fear days; fees are higher too. Managing size and fees matters more than timing sentiment.

Sentiment	Position Size	Daily Trade Cap	Fee Rule
Extreme Fear	Baseline (already elevated)	75% of normal	Track cumulative fees closely
Fear	Baseline	Baseline	Standard
Neutral	Baseline	Baseline	Tighten stops
Greed	Baseline	Baseline	Harvest profits 10–15% earlier
Extreme Greed	−20%	Baseline	Consider short hedge if long% > 65%

Strategy 2 — Segment-Tailored Playbooks

Segment	Priority	Root Cause	Fear Playbook	Greed Playbook
Frequent / Profitable	Monitor	None — preserve edge	Halve leverage; maintain count	+10% allocation; watch fee accumulation
Frequent / Loss-Making	🔴 HIGH INTERVENTION	Fee drag + overtrading	Max 3 trades/day; counter-trend only	Max 1 directional trade; rest in stables
Infrequent / Profitable	Monitor	None — maintain discipline	+15% size on top setups	Standard size; early profit harvest
Infrequent / Loss-Making	🟠 TRAINING NEEDED	No systematic process	Paper-trade / 0.1% risk only	3–4 rule-based trades; 0.5% risk each

Strategy 3 — Short-Bias Awareness & Contrarian Overlay

Given that traders are consistently short-biased (max long% = 40.9% at Greed):

- **Signal:** When `long% < 35%` + `FG Score < 25` → community is maximally short + fearful. Potential long accumulation opportunity in 3 tranches.
- **Signal:** When `long% > 41%` + `FG Score > 75` → crowd is relatively long at Greed peak. Reduce short exposure; avoid chasing.

Output Files

File	Description
`01_metric_distributions.png`	Histograms of 6 key daily metrics with mean/median lines
`02_sentiment_overview.png`	Sentiment class bar chart + FG score fill chart (2023–present)
`03_timeseries_overview.png`	Daily PnL / trade count / win rate time-series coloured by sentiment
`04_fear_vs_greed.png`	Box plots comparing Fear vs Greed across 6 metrics with p-values
`05_behavior_heatmap.png`	Normalised heatmap of 7 metrics across all 5 sentiment classes
`06_fg_score_scatter.png`	Pearson correlation scatter: FG score (0–100) vs PnL, win rate, trade size
`07_directional_bias.png`	Long % by sentiment class + trade size violin plots
`08_segmentation.png`	4-quadrant scatter, win rate bars, fee drag box, segment counts
`09_kmeans.png`	Elbow method + K-Means (k=3) cluster scatter
`10_insight_evidence.png`	Summary evidence for all 5 insights
`11_model_evaluation.png`	Confusion matrix + Random Forest feature importances
`action_matrix.csv`	Segment × Sentiment action playbook (machine-readable)

Reproducibility

Item	Detail
Random seed	`42` throughout
Train/test split	80/20, stratified
Outlier treatment	1st–99th percentile clip on Closed PnL
Timestamp parsing	`dayfirst=True` for `DD-MM-YYYY HH:MM` IST format
Sentiment merge	Left join on `date_only` (day-level)
Open/close filter	`Direction.contains('CLOSE') OR Closed PnL != 0`