Trader Performance vs Bitcoin Market Sentiment

Data Science Assignment Report

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1. Objective

The objective of this project is to analyze the relationship between **Bitcoin market sentiment** (Fear vs Greed) and **trader performance** on the Hyperliquid exchange.
Specifically, the analysis aims to understand how market sentiment influences:

- Trader profitability
- Trading activity
- Risk-taking behavior

The ultimate goal is to extract insights that can inform **smarter, sentiment-aware trading strategies**.

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2. Datasets Overview

2.1 Bitcoin Market Sentiment Dataset

- **Granularity:** Daily
- **Key Columns:**
    - `Date`: Calendar date
    - `Classification`: Market sentiment (Fear or Greed)

This dataset captures overall market psychology and is used as an external explanatory variable.

2.2 Historical Trader Dataset (Hyperliquid)

Each row represents a **single executed trade** on the exchange.

Key columns used:

- `Account`: Unique trader identifier
- `Coin`: Asset traded
- `Execution Price`: Trade execution price
- `Size USD`: Notional value of the trade
- `Side`: Buy (long) or Sell (short)
- `Direction`: Position intent (open or close)
- `Closed PnL`: Realized profit or loss
- `Timestamp IST`: Trade execution time

System-level metadata (transaction hashes, order IDs) were excluded as they do not contribute to analytical insight.

3. Data Preparation & Methodology

3.1 Column Selection

Only columns related to **performance, behavior, risk, and time** were retained.
This prevents noise from exchange metadata and improves interpretability.

3.2 Timestamp Processing

- Trade timestamps were parsed using `dayfirst=True` to correctly handle the DD-MM-YYYY format.
- Trades were aggregated to a **daily level** to align with the daily sentiment index.

3.3 Feature Engineering

Trade-level data was aggregated to an **Account–Date** level to capture daily trader behavior.
The following features were created:

- **Daily PnL:** Sum of realized PnL per trader per day
- **Trades:** Number of trades executed per day
- **Average Trade Size (USD):** Proxy for risk exposure
- **Win Rate:** Fraction of profitable trades
- **Long Ratio:** Proportion of long (buy) trades
- **PnL per Trade:** Activity-normalized performance metric

Normalizing performance by trade count helps avoid bias toward highly active traders.

3.4 Sentiment Integration

Market sentiment was encoded numerically:

- `Fear = 0`
- `Greed = 1`

Trader performance data was merged with sentiment data on the **Date** column.

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4. Exploratory Data Analysis (EDA)

The analysis focuses on how trader behavior and performance differ under **Fear** and **Greed** regimes.

Key visualizations include:

- PnL per trade vs market sentiment
- Trading activity vs market sentiment

(All plots are saved in the `outputs/` directory.)

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5. Key Insights

1. **Trader performance differs across sentiment regimes**
   Risk-normalized profitability (PnL per trade) shows noticeable variation between Fear and Greed periods.
2. **Higher trading activity does not guarantee higher returns**
   Traders tend to trade more during Greed, but increased activity does not consistently translate into better performance.
3. **Risk-adjusted metrics are more informative than raw PnL**
   Normalizing PnL by trade count reveals performance differences that are hidden when using raw profits alone.
4. **Market sentiment influences trader behavior**
   Sentiment appears to affect not only profitability but also how actively traders participate in the market.

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6. Strategy Implications

Based on the findings:

- **During Greed phases:**
  Traders should exercise caution, limit over-trading, and focus on risk control rather than frequency.

- **During Fear phases:**
  Selective participation with disciplined position sizing may offer better risk-adjusted opportunities.

- **Performance evaluation:**
  Trader evaluation should prioritize **risk-adjusted returns**, not absolute PnL.

These insights highlight the importance of adapting trading strategies to prevailing market sentiment.

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7. Limitations

- Market sentiment is represented only as **Fear or Greed**, excluding neutral states.
- Unrealized PnL and liquidation data are not available.
- Broader market variables such as volatility and funding rates are not incorporated.

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8. Future Work

Potential extensions of this analysis include:

- Incorporating volatility and price momentum indicators
- Segmenting traders using clustering techniques
- Applying statistical hypothesis testing
- Building predictive models to estimate profitability under different sentiment regimes

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9. Conclusion

This analysis demonstrates that **market sentiment plays a meaningful role in shaping trader behavior and performance**.

By combining sentiment data with trader-level execution data and using normalized performance metrics, the study provides actionable insights that can support sentiment-aware trading decisions.

Submission Notes

- All analysis was conducted in **Google Colab**
- Cleaned datasets are stored in `csv_files/`
- Visual outputs are stored in `outputs/`
- Code is fully reproducible