Data Science Report: Trader Behavior vs Market Sentiment

1. Executive Summary

Financial markets, particularly cryptocurrency markets, are heavily influenced by collective psychology. Fear and greed often drive decision-making more strongly than fundamentals, leading to inefficiencies, volatility, and opportunities. This project investigates the relationship between **market sentiment** (fear vs greed) and **actual trader behavior** using historical trading data from Hyperliquid and the Bitcoin Fear & Greed Index.

The objective of this analysis is not merely descriptive, but explanatory: to understand how trader profitability, trading volume, and activity patterns change across different sentiment regimes, and how these insights could be applied to smarter, risk-aware trading strategies in a Web3 environment.

This report documents the **full analytical pipeline**, explains the **code logic in detail**, and interprets the **generated outputs and insights** in a practical, business-oriented manner.

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2. Problem Statement and Objective

Crypto markets are known for extreme volatility and strong emotional cycles. While sentiment indicators are widely referenced, they are often used subjectively. This project aims to answer the following core questions:

- How does trader profitability behave during fear vs greed markets?
- Do traders increase risk exposure during specific sentiment regimes?
- Is higher trading activity correlated with better outcomes?
- Can sentiment be treated as a risk signal rather than a profit signal?

By grounding sentiment analysis in **real executed trades**, this project bridges the gap between market psychology and observable trading behavior.

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3. Dataset Description

3.1 Bitcoin Fear & Greed Index Dataset

This dataset captures the emotional state of the broader crypto market on a daily basis. Each row represents one day and includes:

- **Date**: Calendar date of the sentiment reading
- **Value**: Numerical score representing intensity of fear or greed
- **Classification**: Categorical label (Extreme Fear, Fear, Neutral, Greed, Extreme Greed)

This dataset serves as a proxy for **collective market psychology**.

3.2 Historical Trader Dataset (Hyperliquid)

The trader dataset contains granular, transaction-level data reflecting real trading activity. Key fields used in this analysis include:

- **Timestamp**: Execution time of each trade
- **Size USD**: Monetary size of the trade

- **Closed PnL**: Realized profit or loss
- **Side / Direction**: Buy or sell direction

This dataset enables direct observation of trader behavior, risk exposure, and outcomes.

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4. Data Engineering and Code Explanation

4.1 Project Structure and Reproducibility

The notebook begins by programmatically creating a standardized directory structure:

- csv_files/ for intermediate and final datasets
- outputs/ for visualizations and summary outputs

This approach ensures reproducibility, clarity, and compliance with professional data science workflows.

4.2 Data Loading and Validation

The code explicitly checks for the existence of required CSV files before loading them. This defensive programming approach prevents silent failures and mirrors production-grade data pipelines.

Both datasets are loaded into pandas DataFrames, forming the foundation for subsequent processing.

4.3 Data Cleaning and Transformation

Key cleaning steps include:

- Standardizing column names for consistency
- Converting timestamps into human-readable dates
- Removing records with missing or invalid PnL or trade size values
- Ensuring numerical columns are correctly typed

These steps are critical to avoid biased aggregations and misleading insights.

The cleaned trade-level dataset is saved as cleaned_trades.csv, ensuring transparency and traceability.

4.4 Feature Engineering: Daily Trader Metrics

To align trader behavior with daily sentiment data, the code aggregates trade-level data into **daily metrics**, including:

- **Total PnL per day**
- **Average PnL per trade**
- **Total trading volume (USD)**
- **Number of trades executed**

This aggregation transforms raw transactions into interpretable behavioral indicators. The resulting dataset is saved as daily_trader_metrics.csv.

4.5 Merging with Market Sentiment

Daily trader metrics are merged with the Fear & Greed dataset using the date field. This step aligns **what traders did** with **how the market felt** on the same day.

The merged dataset (final_sentiment_trader_dataset.csv) forms the analytical backbone of the project and is suitable for further modeling or strategy research.

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5. Exploratory Data Analysis and Outputs

5.1 Profitability vs Market Sentiment

Output: pnl_vs_sentiment.png

This visualization compares daily total PnL distributions across sentiment classifications. The plot reveals:

- Fear periods exhibit wider PnL distributions
- Higher volatility and inconsistent outcomes during fear-driven markets
- Greed periods show more stable but not necessarily higher profitability

This suggests that emotional stress leads to erratic decision-making.

5.2 Trading Volume vs Market Sentiment

Output: volume_vs_sentiment.png

Trading volume increases noticeably during greed and extreme greed periods. This reflects heightened confidence and willingness to deploy capital. However, increased volume does not automatically translate into higher profitability.

This finding highlights the risk of **overconfidence-driven overtrading**.

5.3 Sentiment Distribution

Output: fear_greed_distribution.png

This chart shows how often each sentiment regime appears in the dataset. Fear-based regimes occur frequently, emphasizing that stressful market conditions are not rare anomalies but a regular feature of crypto markets.

5.4 Summary Metrics Output

Output: sentiment_summary_metrics.csv

This CSV provides recruiter- and business-friendly metrics, including:

- Average daily PnL per sentiment
- Median PnL (robust to outliers)
- Average trade volume
- Average trade frequency

This file enables rapid evaluation without re-running the notebook.

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6. Key Insights and Interpretation

Insight 1: Fear Amplifies Risk

Fear periods show higher PnL dispersion, indicating unstable outcomes. Traders appear more reactive, potentially cutting winners early or holding losers too long.

Insight 2: Greed Increases Exposure, Not Skill

During greed phases, traders increase volume and activity. However, profitability does not scale proportionally, suggesting diminishing marginal returns.

Insight 3: Sentiment Is a Risk Filter

Market sentiment is better used to adjust **risk parameters** rather than to generate directional trades. For example:

- Lower leverage during extreme greed
- Smaller position sizes during extreme fear

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7. Practical Implications for Web3 Trading Teams

- Sentiment-aware risk controls can reduce drawdowns
- Monitoring PnL dispersion provides early warning signals
- Combining sentiment with behavioral metrics improves decision quality

This analysis demonstrates how data science can convert abstract emotions into actionable signals.

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8. Conclusion

This project shows that trader behavior is deeply influenced by market sentiment, but not always in rational or profitable ways. By integrating sentiment data with real trading outcomes, we gain a clearer understanding of when markets are driven by fear, confidence, or crowd behavior.

The analysis emphasizes that **discipline, risk management, and context awareness** are more valuable than emotional alignment with the market. This perspective is critical for sustainable performance in volatile Web3 trading environments.
