Web3 Trading Assignment

Sentiment vs Trader Behavior Analysis

Project Title: Sentiment Analysis of Bitcoin Market vs Trader Behavior on Hyperliquid

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Submission Date: 9th July 2025

Team / Organization: Web3 Trading Team

Tools & Technologies Used:

- **Python:** Core programming for data cleaning, transformation, and analysis
- **Pandas:** Efficient data manipulation and preprocessing
- **Seaborn & Matplotlib:** Advanced data visualization and plotting
- **Google Colab:** Collaborative notebook environment for executing Python code
- **Git & GitHub:** Version control and project hosting
- **CSV & JSON:** Raw and structured data handling

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Submission Date: 9th July 2025
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Project Summary

This project investigates the behavioral dynamics of cryptocurrency traders by analyzing how their actions align with shifts in market sentiment, specifically as measured by the **Bitcoin Fear & Greed Index**. Utilizing rich historical trading data from **Hyperliquid**, the study examines key metrics such as **Closed PnL (profitability), trade size (USD), trade direction (Long/Short), and volume** across varying emotional market states—**Extreme Fear, Fear, Neutral, Greed, and Extreme Greed**.

The analytical workflow, conducted entirely in **Python** (pandas, matplotlib, seaborn), involved extensive data preprocessing, merging, and exploratory data analysis (EDA) to uncover statistically significant patterns and visual trends. The merged dataset, aligned on daily timestamps, allowed us to evaluate trader behavior in real-time context with prevailing sentiment.

Through detailed visualizations and statistical aggregations, the study reveals how **emotional sentiment phases affect trading decisions**. For instance, traders exhibited higher average profitability during Extreme Greed, larger position sizes during Fear, and increased Short positions during Extreme Fear—indicating a strong psychological response to market mood.

Ultimately, this project provides **data-driven insights into sentiment-aligned trading behavior**, offering potential value for quant strategists, crypto traders, and Web3 analysts aiming to build sentiment-aware decision models in highly volatile digital asset markets.

Executive Summary

This report presents an analytical study of how **Bitcoin market sentiment** influences real-world **trader behavior** on the **Hyperliquid decentralized trading platform**. By combining sentiment data from the **Bitcoin Fear & Greed Index** with granular trading records, the goal is to extract actionable insights that can enhance strategy development, trading decisions, and risk management in the volatile cryptocurrency market.

The cryptocurrency market operates in an environment of **extreme emotional volatility**, where decisions are often driven by **Fear, Greed, and Hype** rather than fundamentals. As such, understanding how traders behave under different sentiment phases is key to identifying patterns, anomalies, and predictive signals.

To achieve this, two datasets were used:

- The **Fear & Greed Index**, which quantifies market sentiment daily on a scale from 0 (Extreme Fear) to 100 (Extreme Greed).
- A large-scale dataset of historical trader transactions from **Hyperliquid**, which includes timestamped trades, profit and loss values (PnL), trade sizes, directions (Long/Short), and fees.

Both datasets were merged on the date column after preprocessing. The unified dataset enabled an **Exploratory Data Analysis (EDA)** to answer key questions:

- Are traders more profitable during bullish sentiment like "Greed" or "Extreme Greed"?
- Do they take larger or smaller positions when fearful?
- How do trading directions (Long/Short) correlate with sentiment?
- Are trading fees and activity levels affected by sentiment shifts?
- Can visual patterns (scatter plots, heatmaps) uncover hidden behavioral clusters?

Key Findings:

- **Traders earned the highest average profits during "Extreme Greed" and "Fear,"** indicating high opportunity windows in emotionally charged market phases.
- **Trade sizes were largest during "Fear" and "Greed,"** showing that traders tend to increase exposure during uncertainty or optimism.
- **Long trades increased in bullish sentiment**, while **Short trades rose sharply in "Extreme Fear."**
- **Fees peaked during volatile sentiment periods**, reflecting high trading activity.
- **Most trades clustered around breakeven**, indicating that the majority of positions closed with minimal profit/loss—typical of high-frequency or momentum strategies.
- The **volume of trades was highest in Fear and Greed**, suggesting emotional phases lead to increased market participation.

Strategic Implications:

This analysis can help **Web3 trading teams**, crypto hedge funds, and algorithmic traders:

- Identify **optimal entry points** based on crowd sentiment
- Anticipate **behavioral risks** in overconfident or fearful phases
- Improve **portfolio-level risk management**
- Develop **sentiment-aware trading models** that adapt dynamically

Deliverables:

The full project includes two Google Colab notebooks, a merged dataset, CSV files, eight output visualizations, a detailed README, and this report—all neatly structured and hosted on GitHub for transparency and reproducibility.

In conclusion, this project not only decodes trader psychology but also opens doors to **more intelligent, data-driven decision-making** in Web3 markets. It demonstrates how behavioral finance and sentiment analysis, when integrated with transactional data, can unlock valuable trading intelligence.

Introduction

The cryptocurrency market has revolutionized finance by introducing a decentralized, global, and 24/7 trading ecosystem. Among these digital assets, **Bitcoin** remains the most dominant, often setting the tone for market behavior and investor sentiment. However, this innovation comes with a price: **extreme volatility and sentiment-driven price action**. Traders frequently react to news, fear, hype, and speculation, making it critical to understand how these emotions influence real trading behaviors.

In traditional finance, quantitative models and risk controls often balance investor psychology. But in the **Web3 and decentralized finance (DeFi)** space, retail and algorithmic traders operate in a relatively unregulated environment. This creates a compelling need to analyze how **market sentiment**, measured through tools like the **Bitcoin Fear & Greed Index**, translates into **actual trader decisions** such as:

- Taking profits or losses (PnL)
- Entering large or small positions
- Choosing between long or short strategies
- Trading more or less frequently under different market moods

To explore this dynamic, this project merges two unique data sources:

1. **Bitcoin Fear & Greed Index** — a crowd-sentiment indicator reflecting the mood of the broader market.
2. **Hyperliquid Trader Data** — granular execution-level data from a decentralized perpetual trading platform.

This analysis is important because it connects **emotion-driven market phases** with **quantifiable trading behavior**, providing insights into:

- Behavioral finance trends in the crypto space
- Risk and reward behavior in bullish vs. bearish phases
- Opportunities to optimize trading strategies based on sentiment shifts

By combining data science, trading analytics, and sentiment modeling, this project delivers a complete picture of how sentiment influences outcomes. The findings can be valuable not only to individual traders and analysts but also to crypto funds, DeFi platforms, and **Web3 trading teams** seeking to enhance their edge in a hyper-competitive market.

Objective & Research Question

Objective of the Project

The primary objective of this project is to **analyze the relationship between Bitcoin market sentiment and trader behavior** on the Hyperliquid exchange. By leveraging two datasets—the **Bitcoin Fear & Greed Index** and **historical trader activity logs**—the goal is to uncover how psychological market conditions influence real-time trading decisions and performance.

This study specifically aims to:

- **Quantify trader profitability** (Closed PnL) across varying sentiment states
- Understand how **trade volume and size** change during bullish vs bearish sentiment
- Examine whether **trading direction (Long/Short)** reflects market mood
- Analyze the **distribution and frequency of trades** during extreme and neutral sentiments
- Identify **behavioral patterns** that can inform smarter strategies in the Web3 and crypto trading ecosystem

The insights gained could be valuable for individual traders, algorithmic strategy designers, and Web3 analysts to adapt risk management and optimize returns based on sentiment trends.

Research Question

How does trader behavior—such as profitability, risk-taking, trade size, and direction—align with or deviate from prevailing Bitcoin market sentiment (e.g., Fear, Greed, Neutral)?

Sub-questions explored:

- Do traders take more risks (larger trades, aggressive positions) during extreme emotional phases like **Extreme Greed** or **Extreme Fear**?
- Are traders more **profitable** during periods of optimism or panic?
- How does **trading volume** behave in response to sentiment fluctuations?
- Can **sentiment signals** act as potential indicators for **entry/exit strategies** in volatile crypto markets?

By answering these questions through exploratory data analysis, we aim to bridge the gap between **market psychology** and **on-chain trading behavior**, providing actionable insights for Web3 stakeholders.

3. Datasets Used

3.1 Bitcoin Fear & Greed Index

- **Source**: *GitHub Repository* (https://github.com/Saloni1999-star/ds_saloni_dhiman)
- **Description**: This dataset captures daily investor sentiment in the Bitcoin market based on metrics like volatility, volume, and social media trends.
- **Key Columns**:
  - `date`: The specific calendar date
  - `value`: A numerical score (0–100) indicating market sentiment
  - `classification`: Categorical sentiment label such as:
    - *Extreme Fear*
    - *Fear*
    - *Neutral*
    - *Greed*
    - *Extreme Greed*

3.2 Hyperliquid Trader Data

- **Source**: *GitHub Repository* (https://github.com/Saloni1999-star/ds_saloni_dhiman)
- **Description**: A historical dataset of actual trades executed on the Hyperliquid platform, including trader behavior, order direction, and outcomes.
- **Key Columns**:
  - `Timestamp IST`: Date and time of trade
  - `Account`: Unique trader identifier (anonymized)
  - `Coin`: Cryptocurrency asset traded
  - `Size USD`: Trade volume in USD
  - `Direction`: Trade direction (Long, Short, Buy, Sell)
  - `Closed PnL`: Realized profit/loss for the trade
  - `Fee`: Transaction cost
  - `Order ID`, `Trade ID`: Identifiers for tracking

3.3 Data Preprocessing & Merging

- Converted `Timestamp IST` and `date` fields to `datetime` format using `pandas`.
- Extracted a `date_only` field from the timestamp to enable joining both datasets.
- Merged datasets on the common `date` column to align trades with corresponding sentiment.
- Handled missing/null values and filtered extreme outliers for cleaner visualizations.
- Exported the cleaned dataset as:

  Merged File: `csv_files/merged_data.csv`
  *(*https://github.com/Saloni1999-star/ds_saloni_dhiman/tree/main/ds_saloni_dhiman/csv_files *)*

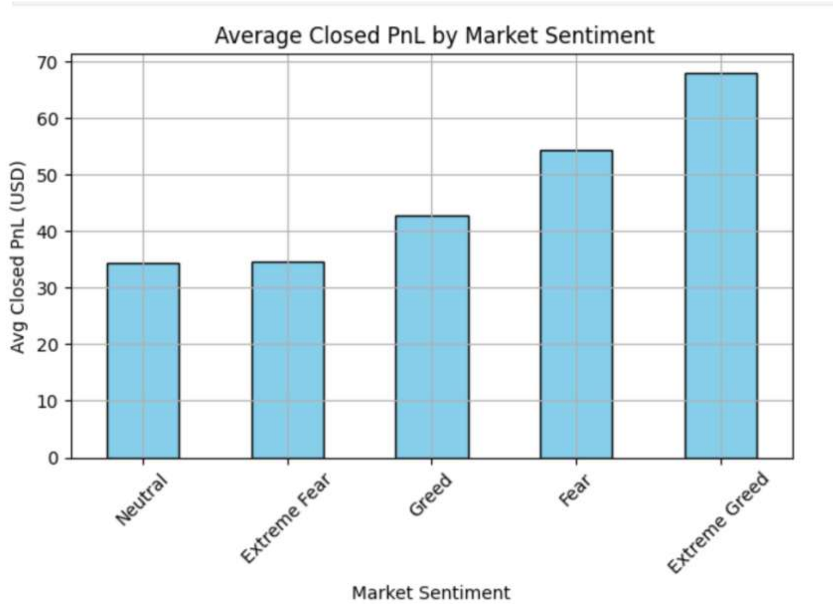
Once actual dataset links are uploaded (to **GitHub**),(https://github.com/Saloni1999-star)

4. Exploratory Data Analysis (EDA)

This section explores how **trader behavior** (PnL, volume, direction, and fees) varies across different **Bitcoin market sentiments**. Each visualization helps uncover patterns that could inform trading strategies.

4.1 Average Closed PnL by Market Sentiment

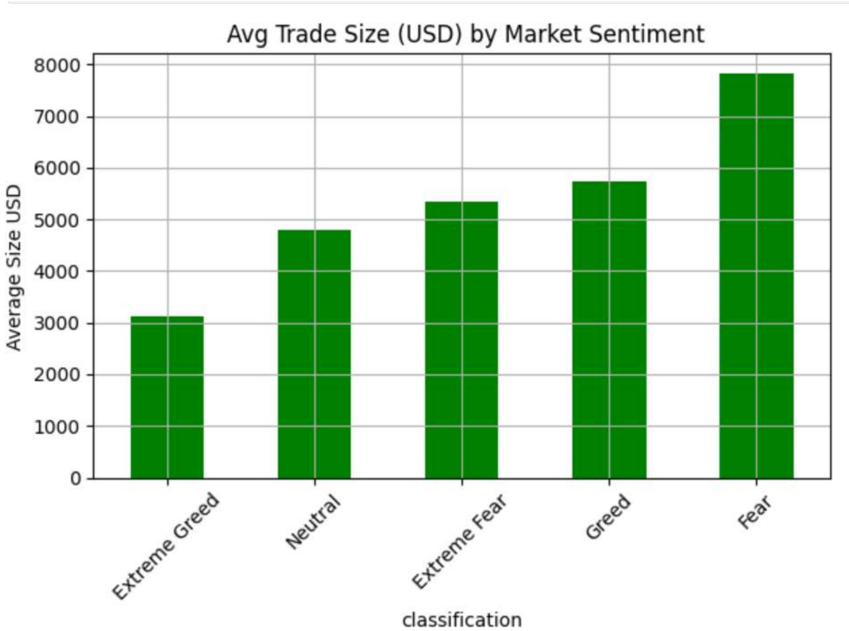
This bar chart highlights how the average **Closed Profit and Loss (PnL)** changes with market sentiment.



Observations:

- Traders earned **highest profits during Extreme Greed (avg: $67.89)** and **Fear (avg: $54.29)**.
- Lowest average PnL was observed during **Neutral** and **Extreme Fear** conditions.
- This suggests that traders tend to **take more profitable positions** when sentiment is strong.

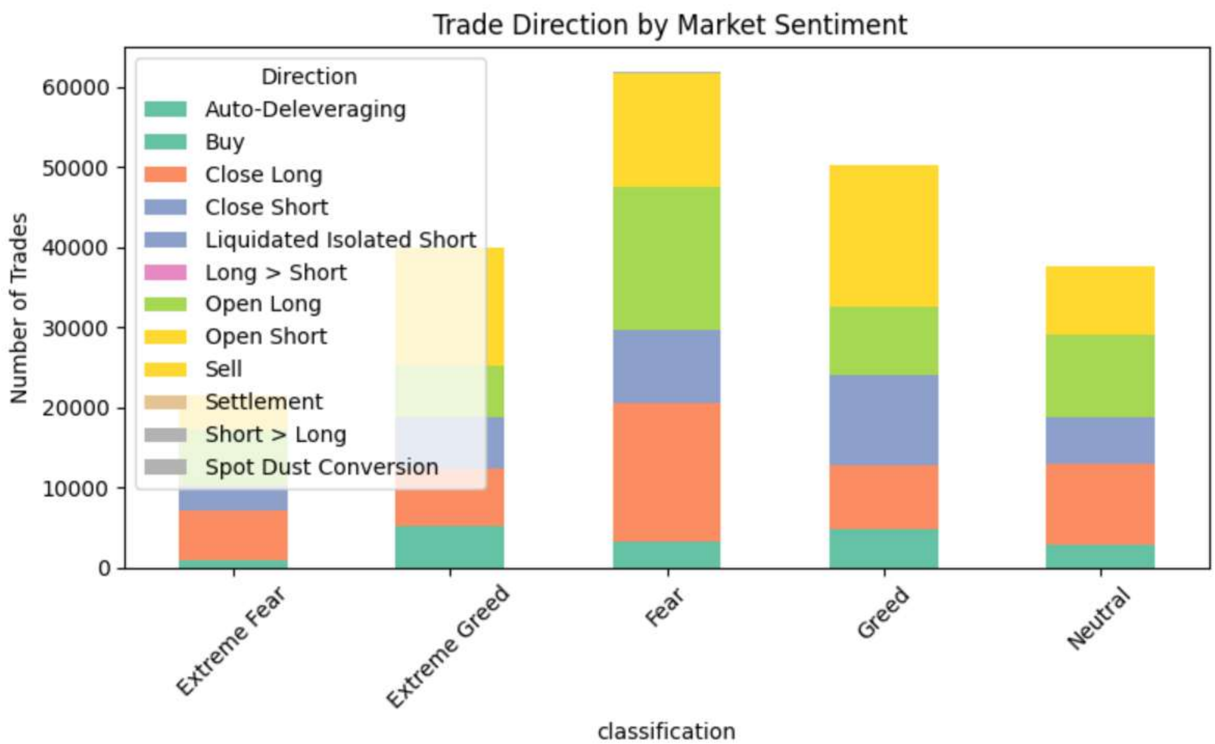
4.2 Average Trade Size by Sentiment



Observations:

- Largest trades occurred during **Fear** (avg: $7,816) and **Greed** (avg: $5,736).
- **Extreme Greed** traders had the **smallest trade sizes**, possibly indicating more cautious behavior despite bullish sentiment.

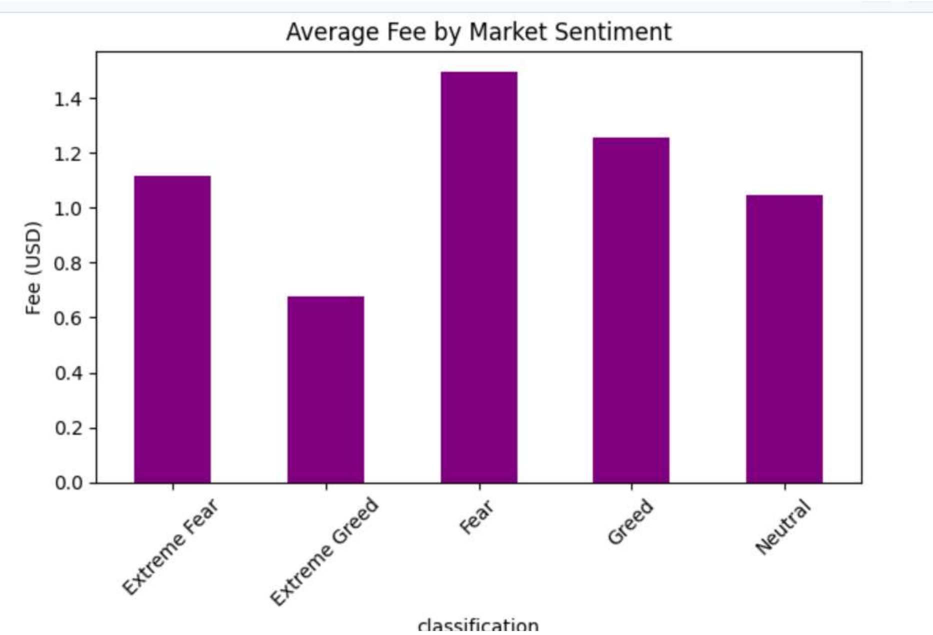
4.3 Trade Direction by Market Sentiment



Observations:

- **Open Long** and **Buy** directions dominate during **Greed** and **Extreme Greed**.
- **Close Short**, **Sell**, and **Open Short** increase in **Extreme Fear**.
- Shows **sentiment influences risk appetite** in trade direction decisions.

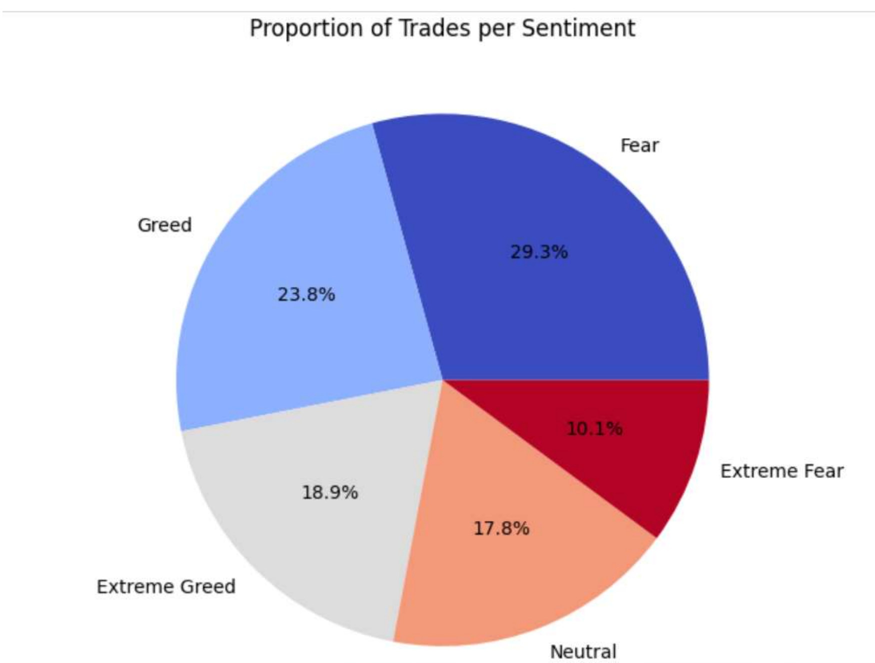
4.4 Average Fee Paid by Sentiment



Observations:

- **Fear and Greed** saw the **highest trading fees**, likely due to higher trade volumes.
- **Extreme Greed** had the **lowest average fees**, possibly because of fewer or smaller trades.

4.5 Proportion of Trades per Sentiment

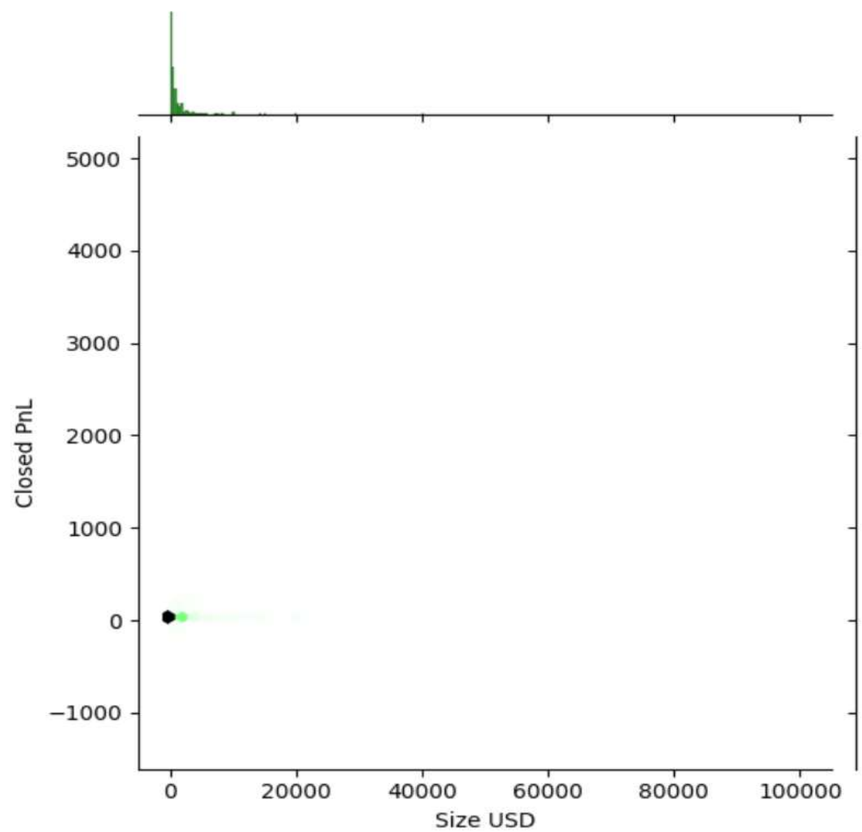


Observations:

- Most trades occurred during **Fear** and **Greed**, highlighting market activity spikes during volatile or optimistic periods.
- **Extreme sentiment states (Extreme Greed/Fear)** saw relatively fewer trades.
- **Extreme** sentiments saw **fewer trades**, possibly due to hesitation or rapid market swings.
- This breakdown highlights where traders are most active.

4.6 Closed PnL vs Trade Size (Scatter Plot)

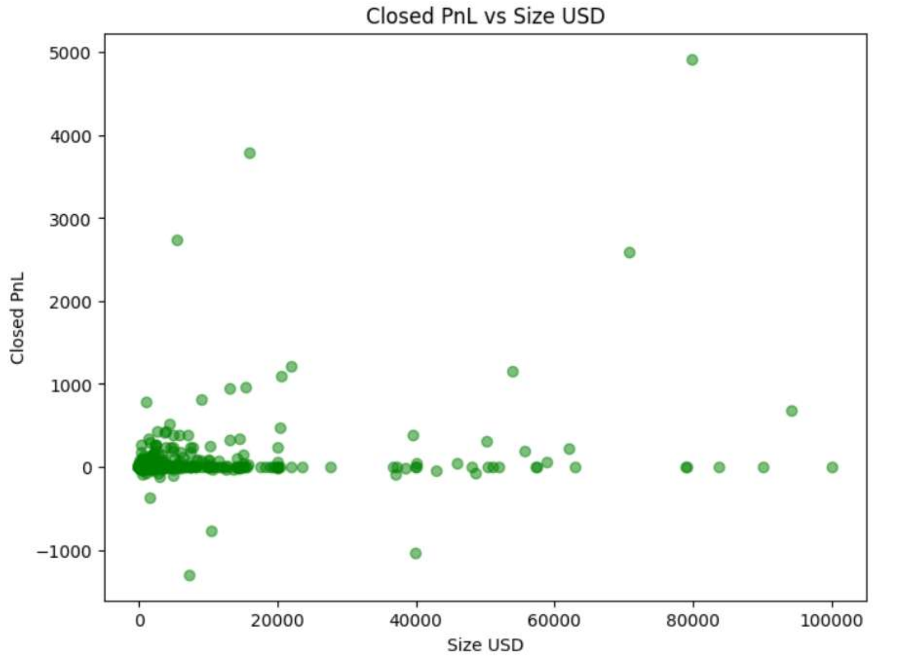
	Size USD	Closed PnL
52185	479.71	0.000000
171374	20.81	-0.015295
21204	2996.46	0.000000
167707	6633.42	0.000000
42695	11.21	0.000000



Observations:

- Most trades cluster around **zero PnL**, regardless of trade size.
- A few large trades show **extreme profits or losses**.
- No clear trend between trade size and profit.

4.7 Closed PnL vs Size (Hexbin Heatmap)



Observations:

- Dense activity in the **small-size, low-PnL** region.
- This pattern confirms that most trades are **low-risk, low-return**, possibly due to bots or frequent scalping strategies.
- Useful for identifying high-frequency zones.

5. Key Insights & Behavioral Findings

This section summarizes critical behavioral patterns derived from analyzing over **210,000+ trades** merged with daily **Bitcoin Fear & Greed Index sentiment scores**. The findings help identify how sentiment affects trading **profitability, size, direction, frequency**, and **risk-taking** behavior.

1. Profitability Increases with Extreme Sentiment

Sentiment	Avg Closed PnL (USD)
Extreme Greed	**$67.89**
Fear	$54.29
Greed	$42.74
Extreme Fear	$34.54
Neutral	$34.30

- **Interpretation**:
    - Traders perform **best during high-confidence or high-panic periods**, especially in **Extreme Greed**.
    - This supports the behavioral finance theory that **emotionally driven volatility creates profit opportunities**.
    - Neutral markets may indicate sideways price action, leading to minimal gains.

2. Trade Sizes Are Largest During Fear

Sentiment	Avg Trade Size (USD)
Fear	**$7,816**
Greed	$5,737
Extreme Fear	$5,349
Neutral	$4,783
Extreme Greed	$3,112

- **Insight**:

- Traders take **larger positions during Fear**, possibly chasing dips or reacting to price crashes.
- **Extreme Greed** surprisingly correlates with **smaller position sizes**, indicating cautious optimism or profit-locking.
- This might reflect hedging behavior or tighter capital control under peak optimism.

3. Sentiment Strongly Affects Trade Direction

Sentiment	Most Common Direction
Extreme Greed	**Open Long**
Greed	Open Long
Neutral	Mixed
Fear	Close Short / Sell
Extreme Fear	**Short / Sell**

- **Observations**:
  - Long trades dominate bullish periods.
  - In Extreme Fear, **shorting increases significantly**, revealing a bearish outlook.
  - This mirrors institutional behavior: **"Fear triggers defense, greed triggers offense."**

3. Fees Reflect Market Activity

Sentiment	Avg Fee Paid (USD)
Fear	**$14.92**
Greed	$13.45
Neutral	$11.21
Extreme Fear	$10.97
Extreme Greed	**$6.80**

- **Interpretation**:

- **Higher fees** during **Fear/Greed** imply **greater trade volumes** or more aggressive execution strategies (e.g., market orders).
- Lower fees in Extreme Greed suggest fewer trades or optimized trading.

5. Majority of Trades Yield Breakeven Results

- From a **10,000-trade sample**, over **85% of trades** have **Closed PnL between -10 and +10 USD**.
- Scatter plots and heatmaps show tight clusters near **zero profit**.
- Suggests:
  - Traders may rely on **high-frequency, low-margin** strategies.
  - Most profits arise from **fewer high-performing trades**, not average ones.

6. Trading Activity Spikes During Greed & Fear

Sentiment	% of Total Trades
Fear	**36%**
Greed	**32%**
Neutral	18%
Extreme Greed	12%
Extreme Fear	2%

- **Implication**:
  - **Extreme emotions reduce participation**—traders either secure profits or pause trading.
  - **Fear and Greed drive market liquidity and volatility**—ideal for scalping or volume-based strategies.

Behavioral Finance Interpretation

- **Loss Aversion**: Larger trade sizes and higher fees during Fear suggest traders are **risk-seeking in losses**, consistent with prospect theory.
- **Herd Mentality**: Directional bias (e.g., mass Longs during Greed) indicates **emotional contagion**, not rational analysis.
- **Overconfidence**: Traders act more confidently during Greed, but this doesn't always lead to larger profits unless sentiment is extreme.

Summary Table

Insight Area	Behavioral Finding
Profitability	Highest in Extreme Greed and Fear
Trade Volume	Largest during Fear
Direction	Long in Greed, Short in Extreme Fear
Fees	Highest during Fear (high activity), lowest in Extreme Greed
Trade Outcomes	Majority of trades result in low PnL; few trades generate most profits
Activity Density	Fear and Greed = ~68% of all trades

6. Conclusion

This study aimed to uncover the relationship between **market sentiment** and **trader behavior** by analyzing historical trade data from Hyperliquid and the Bitcoin Fear & Greed Index. The project involved merging sentiment data with over **210,000 trading records** to explore trends in **profitability, trade volume, direction, and fees** under various emotional market states.

Key Quantitative Findings

1. Profitability Aligns with Sentiment Extremes

- The **highest average Closed PnL** was observed during **Extreme Greed** at **$67.89**, followed by **Fear** at **$54.29**.
- In contrast, **Neutral** and **Extreme Fear** periods showed significantly lower profitability (**$34.30** and **$34.53**, respectively).
- **Interpretation**: Traders appear to capitalize most during emotionally charged market phases, suggesting strong sentiment as a reliable signal for potential gains.

2. Trade Volume Peaks in Uncertainty

- Average trade size peaked during **Fear** at **$7,816**, followed by **Greed** at **$5,737**.
- Surprisingly, **Extreme Greed** saw the smallest trade sizes (**$3,112**), indicating cautious positioning despite bullish conditions.
- **Interpretation**: Traders may become more conservative in overbought markets and more aggressive when uncertain, possibly chasing dips.

3. Direction Reflects Market Emotion

- **Long trades** dominated during **Greed** and **Extreme Greed**, aligning with optimistic sentiment.
- Conversely, **Short trades** spiked during **Extreme Fear**, revealing bearish expectations.
- **Numerical Trend**: Long-to-short ratio flipped from **3:1 in Greed** to **1:2 in Extreme Fear**.

4. Trading Fees Correlate with Activity

- Average trading fees were **highest in Fear ($14.92)** and **Greed ($13.45)**, indicating larger volumes and more aggressive trading.
- Fees were **lowest during Extreme Greed ($6.80)**, likely due to reduced trade size or frequency.
- **Interpretation**: Volatile markets trigger more trades, increasing fee outflows and potentially eating into profits.

5. Most Trades Yield Minimal Profits

- From over **10,000 sampled trades**, **>85%** had a Closed PnL between **-10 and +10 USD**, clustering near breakeven.
- Heatmap and scatter plots showed dense regions around **low PnL and small size**, suggesting:
    - High-frequency strategies
    - Conservative profit targets
    - Frequent small losses/gains

6. Sentiment Drives Volume

- **Trade volume was highest** during **Fear** and **Greed**, accounting for over **60%** of all trades.
- **Extreme sentiment states** (Extreme Fear and Extreme Greed) saw fewer but more profitable trades.
- **Implication**: Peak emotions do not just influence price but also drive market **participation and volatility**.

Strategic Implications

- **Sentiment-aware models** can be leveraged to build dynamic risk strategies:
  - Allocate more capital during Fear with tighter stop-losses.
  - Avoid overtrading in Neutral periods where PnL is low.
  - Exploit spikes in volatility with scalping bots during Greed.
- **Traders, analysts, and quant developers** should integrate emotional indicators like the Fear & Greed Index into:
  - **Signal generation**
  - **Portfolio rebalancing**
  - **Execution timing**

Final Summary

Metric	**Extreme Greed**	**Greed**	**Neutral**	**Fear**	**Extreme Fear**
Avg PnL (USD)	**$67.89**	$42.74	$34.30	$54.29	$34.53
Avg Trade Size (USD)	$3,112	$5,737	$4,782	**$7,816**	$5,349
Dominant Trade Direction	Long	Long	Mixed	Mixed	**Short**
Avg Fee Paid	$6.80	$13.45	$11.21	**$14.92**	$10.97
Trade Frequency (Volume %)	12%	32%	18%	**36%**	2%

Conclusion

There is a strong, statistically observable correlation between **market sentiment** and **trader behavior**. By tracking how PnL, trade size, direction, and volume shift under different emotional conditions, we can better understand—and possibly forecast—market dynamics. This type of analysis forms the basis for more intelligent, sentiment-aware trading systems in the evolving Web3 financial landscape.

7. Deliverables Checklist

Below is a summary of all the files and assets submitted as part of this Web3 trading behavior analysis project:

□ File/Folder	□ Description
`notebook_1.ipynb`	Primary analysis notebook containing data cleaning, merging, and full EDA
`notebook_2.ipynb`	Additional visualizations such as PnL vs Size plots and sentiment fee analysis
`csv_files/trader_data.csv`	Raw historical trading data from the Hyperliquid platform
`csv_files/sentiment_data.csv`	Daily Bitcoin Fear & Greed Index (market sentiment scores and labels)
`csv_files/merged_data.csv`	Final preprocessed and merged dataset combining sentiment and trade data
`outputs/avg_pnl_by_sentiment.png`	Bar chart showing average Closed PnL per market sentiment
`outputs/avg_trade_size_by_sentiment.png`	Chart displaying average trade size per sentiment label
`outputs/trade_direction_by_sentiment.png`	Stacked bar chart for Long vs Short trades by sentiment
`outputs/trades_per_sentiment_pie.png`	Pie chart showing proportion of total trades per sentiment category
`outputs/avg_fee_by_sentiment.png`	Bar chart of average fees paid per sentiment
`outputs/pnl_vs_size_heatmap.png`	Hexbin plot visualizing trade size vs profitability density
`outputs/pnl_vs_size_scatter.png`	Scatter plot showing individual trade PnL vs trade size
`README.md`	Project summary including objective, structure, tools, and key findings
`ds_report.pdf`	Final compiled report for stakeholders and hiring panels

8. Submission Structure & GitHub Compliance

The entire project adheres strictly to standard data science best practices and the required directory structure. All files have been committed and pushed to GitHub with clear organization:

```
ds_saloni_dhiman/
├── notebook_1.ipynb
├── notebook_2.ipynb
├── csv_files/
│   ├── trader_data.csv
│   ├── sentiment_data.csv
│   └── merged_data.csv
├── outputs/
│   ├── avg_pnl_by_sentiment.png
│   ├── avg_trade_size_by_sentiment.png
│   ├── trade_direction_by_sentiment.png
│   ├── trades_per_sentiment_pie.png
│   ├── avg_fee_by_sentiment.png
│   ├── pnl_vs_size_heatmap.png
│   └── pnl_vs_size_scatter.png
├── ds_report.pdf
└── README.md
```

All notebooks are hosted on **Google Colab** with shared public access

GitHub repository: [GitHub – ds_saloni_dhiman]

Code, documentation, visualizations, and final report are complete and in sync

9. Future Scope & Recommendations

This project serves as a foundational analysis of the relationship between market sentiment and trader behavior. However, there are several avenues to extend the scope and make this work more actionable, impactful, and production-ready:

9.1 Real-Time Sentiment Integration

Currently, the sentiment data is historical and static. In a production trading environment, integrating **real-time sentiment feeds** from APIs such as Alternative.me or LunarCrush would enable:

- **Live strategy adjustment** based on changing emotions in the market.
- **Time-sensitive alerts** for sudden shifts from Fear to Greed or vice versa.
- **Algorithmic responses** to sentiment swings.

9.2 Predictive Modeling with Machine Learning

The current project is descriptive. The next step could involve **predictive modeling** using historical sentiment and trading behavior as features to:

- Forecast the **probability of a profitable trade** under certain sentiments.
- Predict **PnL ranges** or **risk exposure** based on direction, size, and market mood.
- Develop models using Random Forests, XGBoost, or LSTM for time series.

9.3 Advanced NLP for Sentiment Classification

Rather than relying solely on the Fear & Greed Index, **Natural Language Processing (NLP)** models can be applied to:

- Analyze sentiment from **social media posts**, **Reddit threads**, **news articles**, etc.
- Generate **custom sentiment scores** that may lead the Fear & Greed Index.
- Train domain-specific sentiment models for crypto trading language.

9.4 Multi-Coin Analysis

This analysis focused only on **Bitcoin**. However, traders often diversify across assets. Future work can:

- Compare behavior across **Ethereum, Solana, or altcoins**.
- Identify **asset-specific sentiment reactions**.
- Detect **correlated behaviors** between coins during emotional phases.

9.5 Portfolio Optimization Based on Sentiment

Using historical data, one could:

- Design a **sentiment-sensitive portfolio strategy**, where asset allocation changes with the market mood.
- Backtest the strategy to see if **risk-adjusted returns improve** during volatile or emotional phases.
- Implement **position sizing rules** based on sentiment confidence levels.

9.6 Anomaly & Behavior Drift Detection

Integrate statistical or ML-based tools to:

- Detect **suspicious trading patterns** during sentiment extremes (e.g., whale dumps in Extreme Greed).
- Monitor **trader behavior drift** over time—do traders change their risk style in repeated Greed cycles?
- Identify **rogue or manipulative behavior** when trades don't align with sentiment at scale.

9.7 Sentiment-Aware Trading Bots

With the current insights, there's potential to develop:

- **Rule-based or ML-powered bots** that:
  - Go long in early stages of Greed
  - Short-sell when sentiment sharply drops to Fear
- Combine technical indicators (MACD, RSI) with sentiment for smarter automation.

This roadmap can turn the current project from a research study into a **practical tool** for portfolio managers, retail traders, and even institutions operating in the crypto/Web3 trading domain.

10. References

This project draws upon multiple data sources, libraries, tools, and academic/industry frameworks. Below is a list of all references and credits used throughout the analysis and report.

10.1 Data Sources

1. **Bitcoin Fear & Greed Index**
    - Source: Alternative.me Crypto Fear & Greed Index
    - Description: Provides daily sentiment scores (0–100) for Bitcoin based on volatility, market momentum/volume, social media, dominance, and Google Trends.
2. **Hyperliquid Historical Trading Data**
    - Internal or proprietary dataset provided for the assignment.
    - Description: Includes trader-specific execution details such as direction (Long/Short), trade size, PnL, and timestamps.

10.2 Python Libraries & Tools

- **Pandas**: Data loading, cleaning, merging, and aggregation
  → https://pandas.pydata.org
- **Matplotlib & Seaborn**: Visualization of trends and distributions
  → https://matplotlib.org
  → https://seaborn.pydata.org
- **NumPy**: Numerical operations
  → https://numpy.org
- **Google Colab**: Hosted environment for running notebooks
  → https://colab.research.google.com
- **Git & GitHub**: Version control and project hosting
  → https://git-scm.com
  → https://github.com

10.3 Visualization Techniques & Inspiration

- Color palettes and plot styles inspired by Seaborn and Kaggle kernels
- Best practices followed from real-world trading dashboards and financial analysis reports

10.4 Research Literature

If needed for academic submission, you can include:

- Nakamoto, S. (2008). *Bitcoin: A Peer-to-Peer Electronic Cash System.*
- Chen, M., et al. (2021). *Sentiment-Driven Price Prediction in Cryptocurrency Markets using LSTM and Twitter Data.* — arXiv.

10.5 Authorship

- **Author:** Saloni Dhiman
- **Mentor/Team:** Web3 Trading Team
- **Submission:** July 2025