

# Data Science Report

## Analyzing Trader Behaviour vs Market Sentiment (Fear & Greed)

### 1. Introduction

The objective of this project is to analyze how trader behaviour changes with overall market sentiment in the Bitcoin market. Market sentiment is represented using the Fear & Greed Index, which classifies days as either **Fear** or **Greed**. Trader behaviour is extracted from historical trading data from Hyperliquid.

The goal is to understand whether traders behave more aggressively, profitably, or cautiously depending on sentiment, and to identify patterns that could help build smarter trading strategies in Web3 trading systems.

### 2. Datasets

Two datasets are used:

#### **Trader Dataset**

Contains historical trades with information such as:

- account (trader ID)
- symbol
- execution price
- size
- side (BUY/SELL)
- time
- closed PnL
- fees

This dataset helps measure profitability, volume, risk, and activity of traders.

#### **Market Sentiment Dataset**

Contains:

- date
- classification (Fear / Greed)

This dataset describes the emotional state of the market on each day.

### 3. Problem Statement

We aim to answer the following core question:

**How does trading behaviour (profitability, volume, activity, and risk) change under Fear vs Greed market conditions?**

Specifically:

- Do traders trade more during greed?
- Are profits higher in fear or greed?
- Does risk increase during greed?
- Is win rate affected by sentiment?
- Are traders more aggressive or cautious depending on sentiment?

## 4. Data Cleaning & Preparation

Steps performed:

- standardized column names
- removed duplicates
- converted timestamps to datetime
- handled numeric conversions
- engineered features:
  - notional value
  - net PnL
  - PnL percentage
- extracted daily metrics
- aggregated trader behaviour by day
- aligned both datasets by date
- merged trading metrics with sentiment labels

This ensures both datasets speak the same **time-based language**.

## 5. Feature Engineering

Important features created:

- **Notional Value** = execution price × size
- **Net PnL** = closed PnL – fees
- **PnL %** = net PnL / notional value
- **Trades Count** per day
- **Win Rate** = % profitable trades
- **PnL Volatility (Risk)** = standard deviation of PnL
- **Average Trade Size**
- **Total Volume Traded**

These features represent **profitability, risk, volume, and behaviour**.

## 6. Methodology

1. Aggregate trader behaviour by **daily frequency**.
2. Merge daily trading metrics with Fear/Greed sentiment.
3. Compare Fear vs Greed using:
  - o average volume
  - o average PnL
  - o win rate
  - o trade count
  - o risk (PnL volatility)
4. Visualize patterns and relationships.
5. Interpret business meaning from the results.

## 7. Key Questions & Answers

### Q 7.1. Do traders trade more during Fear or Greed?

**Answer:**

From the activity and volume plots, traders tend to trade **more frequently and with higher volume during Greed periods**. This indicates confidence and risk-taking behaviour when the market sentiment is positive.

### Q 7.2. Is profitability higher during Fear or Greed?

**Answer:**

Total and average PnL is generally **higher during Greed days**, meaning optimistic sentiment aligns with better performance. However, some Fear days show sharp losses, indicating panic trading.

### Q 7.3. Does risk increase with sentiment?

**Answer:**

PnL volatility is noticeably higher during **Greed**, showing traders take larger and riskier positions. Fear periods show more cautious and smaller fluctuations.

### Q 7.4. Is win rate affected by sentiment?

**Answer:**

Win rate is slightly higher during **Greed**, suggesting that confidence-driven trading performs better on average than panic-driven behaviour.

### Q 7.5. How does trade size change with sentiment?

**Answer:**

Average trade size increases during **Greed**, indicating higher leverage and stronger conviction when the market is optimistic.

## **Q 7.6. Are traders over-trading during Greed?**

**Answer:**

Yes. Trade count per day rises during Greed, suggesting some level of **overconfidence and higher participation**.

## **Q 7.7. What hidden signals are observed?**

**Answer:**

- High activity does not always guarantee profit.
- Greed increases both **reward and risk**.
- Fear often leads to defensive positioning.
- Some traders lose more during Fear due to panic exits.

These signals can guide smarter algorithmic strategies.

## **8. Visual Insights Explanation**

Each visualization explains a behaviour:

- **Volume by Sentiment** → confidence level
- **PnL by Sentiment** → performance quality
- **Win Rate by Sentiment** → consistency
- **Activity by Sentiment** → participation behaviour
- **Risk vs Return Plot** → aggressiveness

They show how emotion impacts rational trading.

## **9. Business Impact**

This analysis can help trading platforms:

- detect over-trading during Greed
- reduce exposure during Fear
- design sentiment-aware risk management
- optimize leverage usage
- improve trader education and strategy design

Sentiment-driven signals can improve **portfolio stability and alpha generation**.

## **10. Limitations**

- Sentiment is daily, trades are intraday.
- No direct leverage column in dataset.
- Dataset period is limited.
- Trader psychology is simplified into Fear/Greed only.

## **11. Future Enhancements**

- include leverage and liquidation metrics
- build predictive models
- classify traders by behaviour
- add time-series forecasting
- detect regime shifts
- automate sentiment-based strategy signals

## **12. Conclusion**

This project demonstrates that market sentiment strongly influences trader behaviour. Greed leads to higher activity, volume, profit, and risk, while Fear encourages caution but can cause panic losses. By combining behavioural analytics with sentiment signals, Web3 trading platforms can design smarter, safer, and more profitable strategies.