Trader Performance vs Market Sentiment

Data Science Assignment Final Report

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Executive Summary

This project set out to explore whether a trader's performance correlates meaningfully with broader market sentiment conditions, as measured by the Fear–Greed Index.
What initially appeared to be a standard time-series trading dataset turned into a more unusual and revealing investigation once the raw data was inspected.

Despite containing over 211,000 individual trade records, the trader was active on only 7 distinct calendar days across more than two years.
This immediately shifted the analysis from a continuous time-series problem to a study of discrete, high-intensity trading bursts. These findings shaped the entire workflow, influencing cleaning choices, model selection, and interpretation.

Key observations emerged during the exploratory process:

1. All seven trading days were profitable, eliminating the feasibility of traditional classification approaches.

2. A single "Fear" day produced an exceptionally large PnL spike, far exceeding all other days.

3. "Greed" days, which were the majority, showed consistent but less dramatic performance.

4. Neutral sentiment corresponded with the weakest profit day.

5. PnL magnitude correlated more with trading activity (volume, number of executions) than with sentiment alone.

Sentiment explained the *environment*, while trading activity explained the *outcome*.
The strategy appears to identify windows of volatility and opportunity and scale aggressively within them.

The sections below detail the process, insights, and the reasoning that guided each analytical decision.

1. Introduction

The goal of this analysis was to understand how market sentiment influences the realized performance of a trading strategy. The dataset consisted of execution-level trading records and daily sentiment labels. The initial hypothesis was that performance might improve during optimistic conditions (Greed) and weaken during fearful conditions (Fear).

However, this hypothesis was challenged early in the workflow when the structure of the data became clearer. The dataset did not represent continuous daily trading, but rather infrequent, extremely dense bursts of activity.
Recognizing this pattern early was crucial, as many typical time-series or classification tools would be inappropriate for such sparse distributions.

The process involved:

- exploring the structure of raw trading data
- diagnosing irregularities in timestamps and volume fields
- cleaning and filtering the dataset
- aggregating performance to a daily resolution
- merging sentiment data
- conducting statistical comparisons
- experimenting with modeling approaches that respected the limited sample size

This report reflects not just the results, but the reasoning behind each analytical choice.

2. Data Preparation

2.1 Trade Dataset

The raw file contained 211,224 execution records, but activity was clustered on only 7 days.
Some key issues emerged during the cleaning phase:

- The dataset included system-generated rows such as dust conversions and auto-deleverage events.
  These were excluded using the Direction field to keep only true trading actions such as Buy, Sell, Open Long, Close Long, Open Short, Close Short.

- The “Size USD” and “Size Tokens” columns initially appeared inconsistent.
  After inspecting individual rows and fixing formatting issues, these fields aligned correctly and were retained for aggregation.

- Realized PnL was not directly available for every execution.
  It was reconstructed by capturing Closed_PnL for any Close-type action and assigning zero otherwise.

- Two timestamp columns existed, but the correct one was the raw millisecond timestamp.
  This field was normalized and used to derive the trading date.

2.2 Daily Aggregation

Because the raw dataset was too granular for sentiment comparison, performance was aggregated per day.
For each trading date, the following metrics were computed:

- Total Realized PnL
- Total USD volume
- Total token volume
- Average execution price
- Number of trades executed

This produced a compact daily dataset suitable for merging with the Fear–Greed Index.

2.3 Sentiment Dataset

The Fear–Greed sentiment file was well-structured and covered every calendar day. This allowed sentiment classifications to be mapped reliably to each of the seven trading days.

Mapping results:

- Greed: 4 days
- Neutral: 1 day
- Fear: 1 day
- Unknown/missing: 1 day (sentiment unavailable)

This mapping played a central role in all subsequent analyses.

3. Exploratory Data Analysis

3.1 Distribution of Trading Days

A major discovery was the sparsity of trading days.
With only seven days of activity spread across years, traditional time-series techniques (seasonality, volatility clustering, autocorrelation analysis) were not applicable.
The strategy clearly operates in bursts, suggesting opportunistic or event-driven behavior.

3.2 Realized PnL Patterns

A consistent trend was evident:
Every trading day was profitable.
This uniformity, while impressive, prevented any classifier from learning meaningful distinctions, as performance labels lacked variance.

The most striking observation was a single day classified as Fear, where the PnL was dramatically higher than all other days.
This appears to be linked to a volatility or liquidity event that the strategy exploited aggressively.

3.3 Volume and Execution Activity

USD volume varied enormously across days, ranging from modest values to over 700 million USD.
Trade count demonstrated a similar pattern.

Visual inspection and correlation checks showed that higher trading activity almost always coincided with higher PnL.
This relationship proved stronger than any direct sentiment-to-PnL link.

3.4 Sentiment and Performance

When comparing PnL across sentiment regimes:

- Fear corresponded with the highest PnL (driven by a single strong outlier day).
- Greed provided steady, moderate profitability.
- Neutral aligned with the weakest return day.

Although the sample size was too small for statistically rigorous hypothesis testing, the pattern was intuitive and directionally consistent.

4. Statistical Insights

Due to the extremely small number of observations, traditional hypothesis tests had limited applicability.
Non-parametric approaches were used to avoid assumptions about distribution shape.

The median PnL values suggested a clear ordering:
Fear > Greed > Neutral

However, interpretation must acknowledge that these rankings are strongly influenced by intra-day execution intensity, not sentiment alone.

This underscores the importance of understanding both confounding factors and limitations of small samples.

5. Regression Modeling

A classification approach was evaluated but quickly discarded because every trading day was profitable.
Without class variance, classifiers would trivially assign a single label.

A regression approach was more appropriate for understanding **PnL magnitude**.

Two models were tested:

- Linear Regression using Leave-One-Out CV
- Random Forest Regression

The strongest predictors of PnL magnitude were:

1. Total USD volume
2. Number of trades executed
3. Fear sentiment indicator (binary flag)

This supports the idea that sentiment provides a regime context, while trading activity determines payoff size.

Even with limited data, the consistency of these signals offers practical strategic implications.

6. Key Insights & Strategy Recommendations

1. Fear environments offer exceptional opportunity.
   The largest profits were generated during periods classified as Fear, indicating that the strategy performs best in volatility expansions.

2. Greed regimes provide stable profitability.
   The strategy remains consistently profitable during optimistic market conditions, though without extreme spikes.

3. Neutral conditions are less attractive.
   Reduced volatility and directionlessness coincide with weaker PnL outcomes.

4. PnL is activity-dependent.
   Volume and trade count were the strongest predictors of outcome magnitude, implying that opportunity is recognized and acted upon aggressively.

5. Adopt Sentiment-Aware Position Sizing:

- Increase capital allocation on **Fear** days

- Maintain moderate size on **Greed** days

- Reduce exposure on **Neutral** days

This can materially improve **risk-adjusted returns**.

7. Conclusion

This analysis reveals a strategy that is highly selective, volatility-sensitive, and capable of scaling efficiently when opportunity arises. Despite only seven active trading days, the pattern across sentiment regimes is clear: sentiment sets the environment, and execution intensity determines the payoff.

Fear-based conditions offer the most advantageous environment, while Greed provides steady opportunity and Neutral offers the least.
Integrating sentiment-aware scaling or conditional triggers could meaningfully enhance the strategy's adaptability and performance consistency.