Trader Behavior and Market Sentiment Analysis

Web3 Trading Team - Data Science Assignment Report
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Platform: Google Colab

1. Objective

The goal of this assignment is to understand how trader behavior is influenced by overall market sentiment. By combining real trade data with a daily sentiment index, I aim to identify trader personas, quantify behavioral metrics like risk appetite, and assess alignment with crowd sentiment.

2. Datasets Overview

a. historical_data.csv

This dataset contains actual trader transaction records

- account: Wallet address of the trader.
- coin: Token being traded.
- execution price: The price at which the trade occurred.
- size tokens: Quantity of tokens traded.
- size usd: Value of the trade in USD.
- side: Trade direction (BUY or SELL).
- timestamp ist: Time of trade in IST.
- closed pnl: Profit/Loss from trade.
- Other IDs like trade id, transaction hash, etc. that are mostly used for traceability

b. fear_greed_index.csv

This dataset provides market sentiment for each day like fear,greed,neutral for each date:

- Timestamp and date: Date of the sentiment index.
- value:Numerical Score(which is not directly used here).
- classification: Sentiment label (e.g., Greed, Fear).

3. Merging of the two Datasets

Since the historical_data.csv had the timestamp of each trade, I extracted the date and used it to merge with the sentiment data, which also had a date column.

This allowed me to tag each trade with the corresponding market sentiment on that day that helped me create a link between how people traded and what the market mood was.

4. Feature Engineering

To gain deeper insight, the following features were derived:

- **profit_margin = closed pnl / size usd** (This helps normalize the profit regardless of trade size. and It tells how efficient a trade was)

A normalized metric to assess trade efficiency.

- **risk_score = size usd** (says how risky the trade was)

Higher trade values imply higher exposure and risk.

- **is_profitable = closed pnl > 0**(A quick way to label a trade as wins or losses,for calculating success rates)

Boolean flag to track success.

- **holding_bias**

  This measures whether a trader aligned their action with market sentiment:

  - **Aligned:** BUY during Greed, SELL during Fear.
  - **Misaligned:** BUY during Fear, SELL during Greed.

These features helped evaluate both rational and emotional behavior.

5. Trader Profiling using Clustering

Grouped traders based on:

- Average profit margin
- Average risk score
- Success ratio
- Total trades

These were scaled and clustered using KMeans (k=4), that resulted in 4 trader archetypes:

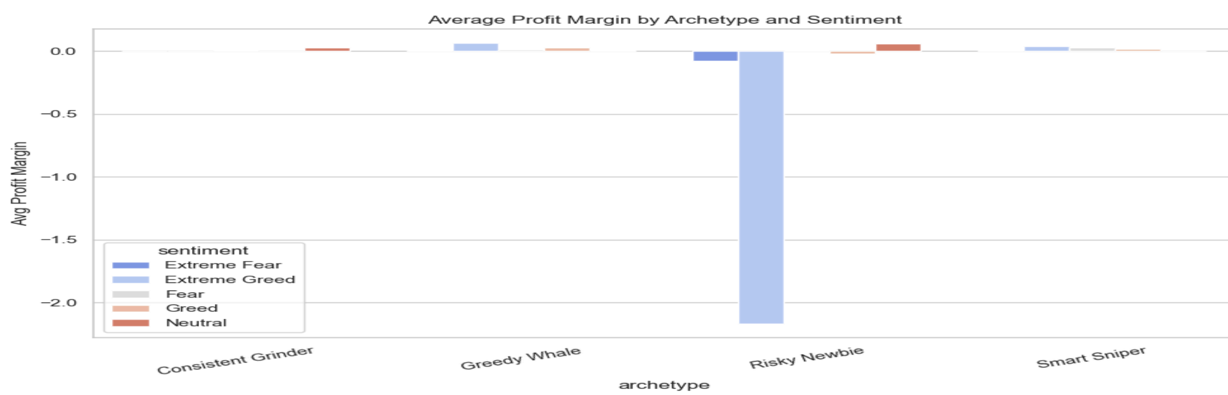
- **Smart Sniper**: Low risk, high reward
- **Greedy Whale**: High volume, high variance
- **Consistent Grinder**: Moderate risk with stable returns
- **Risky Newbie**: Low trades, negative returns

6. Sentiment vs Archetype Analysis

Grouped data by sentiment and archetype to find average profitability and success rates. Key insights:

- Risky Newbies performed better in Fear.
- Greedy Whales excelled in Greed and Neutral.
- Smart Snipers were most consistent across moods.

Visuals: Bar charts comparing avg_profit_margin and success_rate across archetypes



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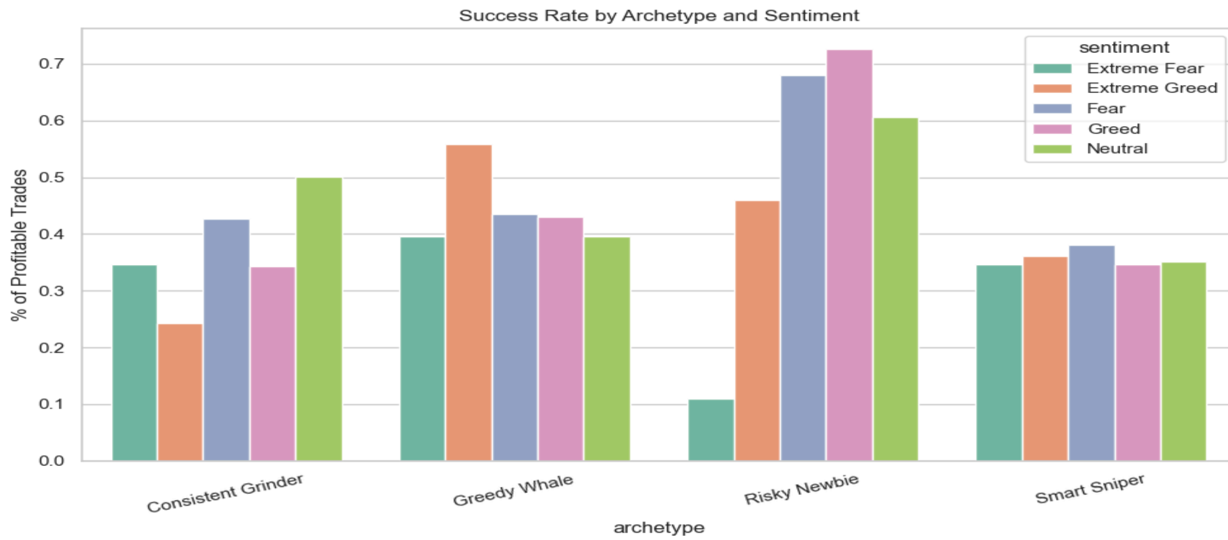


7. Risk-Reward Quadrant Mapping

Created a 2x2 quadrant:

- Axes: Low/High Risk vs Low/High Reward
- Result: 4 quadrants (e.g., High Risk / High Reward)

Sentiment was mapped across these quadrants to reveal that:

- **Extreme Fear** had more trades in High Risk / Low Reward.
- **Greed** and **Neutral** saw more in Low Risk / High Reward.

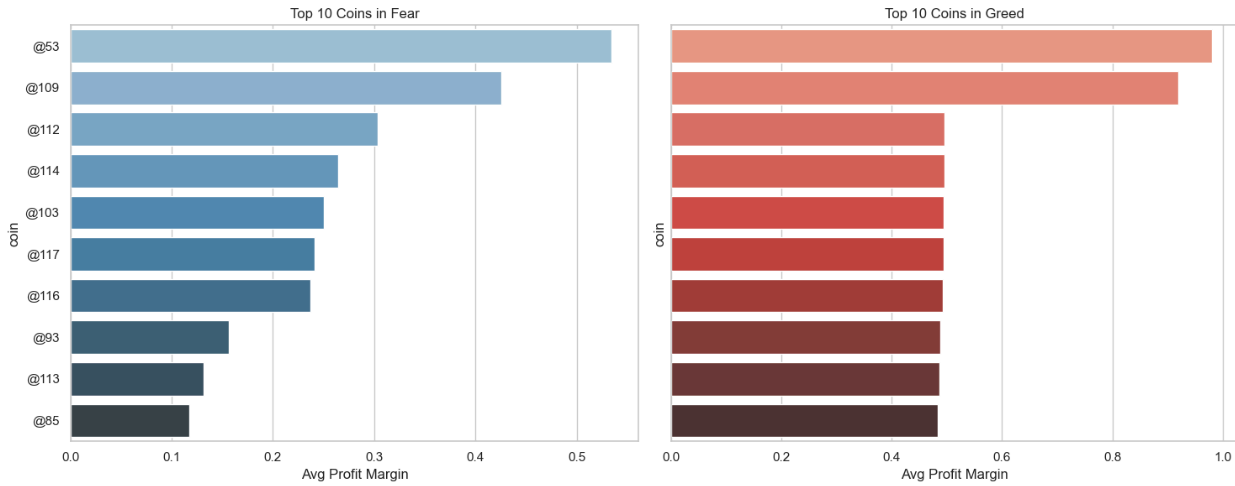
Visuals: Heatmap showing distribution by sentiment and quadrant.

8. Coin Performance by Sentiment

Identified top 10 coins under Fear and Greed based on average profit margins.

- Coins like @1 and @10 performed differently depending on sentiment.
- Helps traders or platforms to recommend tokens based on crowd mood.

Visuals: Bar charts of top coins by sentiment.



9. Summary of Thought Process

- I tried to think like a trader and observe like a data scientist.
- I didn't just want numbers but wanted to extract the behavior.
- So I grouped, normalized, categorized, and cross-compared behavior under different emotional market states.
- I then mapped everything back visually through graphs, bar plots, and heatmaps.

So, I wanted to go beyond the basic analytics and ask questions like:

- Does trader psychology align with market mood?
- Can we classify traders like we do with personality types?
- Is high profit always high risk?

That's why I engineered behavioral metrics, used clustering for archetypes, and visualized the interplay of risk, reward, and emotion.

10. Conclusion

This exercise successfully combined financial data and psychological sentiment. The insights derived can be used by exchanges or strategy platforms to:

- Better understand trader behavior
- Recommend risk-aware strategies
- Align coin recommendations with crowd emotion

All notebooks, outputs, and CSVs have been uploaded in the standardized folder structure as per instructions.