1) Problem Statement

Financial markets are highly influenced by **human emotions** such as fear and greed. At the same time, traders make buy and sell decisions that lead to **profits or losses.** So , we aim to understand how Trader's Sentiment's (**Fear vs Greed)** affect trader behavior and trader performance. So, using given datasets we aim to :

- Analyze how traders perform during **fearful** vs **greedy** market conditions .
- Identify patterns in **profit, loss, leverage, and trading activity.**
- **Derive insights that can help in building smarter trading strategies.**

2) Dataset overview

Fear_Greed_Index:- This dataset represents the **emotional state** of the trader on different trades on different dates.

columns	description
timestamp	Unix timestamp (in seconds) representing the date on which the market sentiment was recorded.
value	Numerical score (0–100) indicating the intensity of market sentiment, where lower values represent fear and higher values represent greed.
classification	Categorical label describing the market emotion for the day (e.g., Fear, Extreme Fear, Greed).
date	Human-readable calendar date corresponding to the sentiment record.

Historical_data:- This dataset captures **actual trader behavior and performance** on the exchange.

columns	description
account	Unique identifier for a trader.
symbol	Trading pair (e.g., BTC-USD).
execution price	Price at which trade was executed.
size	Quantity traded.
side	Buy or Sell direction.
time	Timestamp of the trade.
start position	Position before the trade.

event	Type of trade(open/closed)
closedPnL	Profit or loss after closing the trade.
leverage	Borrowed multiplier used in the trade.

3) Data Preparation & Merging Strategy

3.1) Understanding Data Granularity

The Bitcoin Market Sentiment dataset provides **daily-level sentiment information**, representing the overall market emotion (Fear or Greed) for each day. In contrast, the Historical Trader dataset contains **trade-level records**, where each row corresponds to an individual trade executed at a specific timestamp. Since sentiment data is available only at a **daily granularity**, it is not meaningful to directly align it with trade timestamps at the second or millisecond level. Therefore, both datasets must be brought to a **common daily time scale** before merging.

3.2) Timestamp Standardization

To ensure correct alignment between the two datasets, timestamps from both tables were converted into a **common date format**:

- The sentiment dataset's Unix timestamp (in seconds) was converted into a calendar date.
- The trade dataset's Unix timestamp (in milliseconds) was also converted into a calendar date.
- A new column named **`join_date`** was created in both datasets, representing the date on which the sentiment or trade occurred.

This approach ensures that all trades executed on a given day are associated with the **same overall market sentiment for that day**.

3.3) Data Merging Approach

The two datasets were merged using a **left join**, with the trade dataset as the base table and **`join_date`** as the join key.

The rationale for using a left join is:

- All trade records are preserved.
- Sentiment information is attached wherever available.
- Trades without corresponding sentiment data are retained but marked with missing sentiment values.

This approach avoids unintended loss of trade data and maintains data integrity.

3.4) Creation of Sentiment-Aligned Analysis Dataset

After merging, some trades did not have corresponding sentiment data due to date mismatches between the two datasets.Rather than removing these records permanently, a **separate analysis-ready dataset** was created that includes **only trades with available sentiment information**.

This allows:

- Accurate sentiment-based analysis.
- Preservation of the original merged dataset for reference and traceability.
- Clear separation between raw data and analysis data.

3.5) Resulting Prepared Dataset

The final sentiment-aligned dataset contains:

- Trade execution details.
- Market sentiment classification (Fear or Greed).
- Sentiment intensity value.
- Derived features used for analysis (trade outcome, risk proxy).

This prepared dataset serves as the foundation for all subsequent analyses, including profitability comparison, risk assessment, behavioral analysis, and visualization.

4) Feature Engineering

Feature engineering was performed to transform raw trade and sentiment data into meaningful metrics that help analyze trader behavior and performance under different market sentiments.

4.1) Trade Outcome Classification

Each trade was classified based on its realized profit or loss (`ClosedPnL`):

- Trades with positive closedPnL were labeled as **Win.**
- Trades with negative closedPnL were labeled as **Loss.**
- Trades with zero closedPnL were labeled as **Breakeven.**

This classification helps compare winning and losing trades under Fear and Greed market conditions.

4.2) Risk Proxy Definition

Since explicit leverage information was not available in the dataset, **trade size in USD (`Size USD`)** was used as a proxy for risk.

Larger trade sizes indicate:

- Higher capital exposure
- Greater potential profit or loss
- Increased risk-taking behavior

This risk proxy allows analysis of how traders adjust risk under different market sentiments.

4.3) Sentiment Simplification

Market sentiment categories were simplified to improve clarity of analysis:

- **Extreme Fear** and **Fear** were grouped as **Fear.**
- **Extreme Greed and Greed were grouped as Greed.**

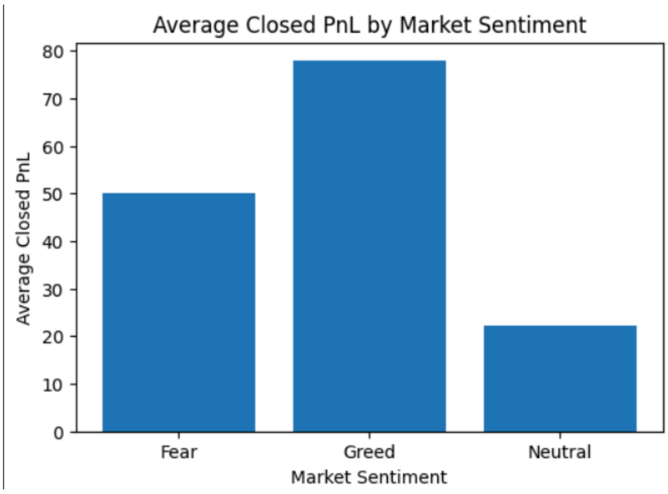
This simplification enables direct comparison of trader behavior and performance between Fear-driven and Greed-driven market conditions.

5) Analysis Framework

To explore the relationship between trader performance and market sentiment, a structured analysis framework was designed. Each step focuses on a specific aspect of trader behavior under **Fear** and **Greed** market conditions.

5.1) Average Profit and Loss by Sentiment

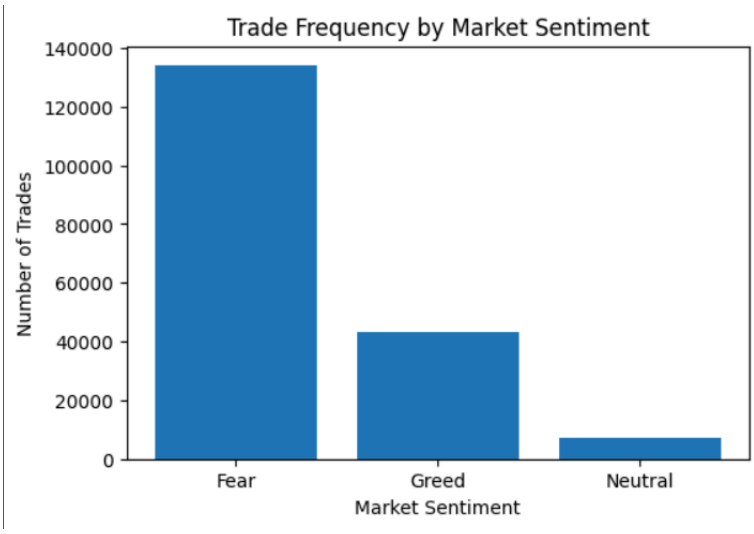
The average realized profit or loss (`ClosedPnL`) was calculated separately for Fear and Greed market conditions.This step helps understand **how market sentiment directly impacts trader profitability** and identifies which sentiment is generally more favorable for making profits.



5.1.a) Avg ClosedPnL vs Market Sentiment

5.2) Trade Frequency by Sentiment

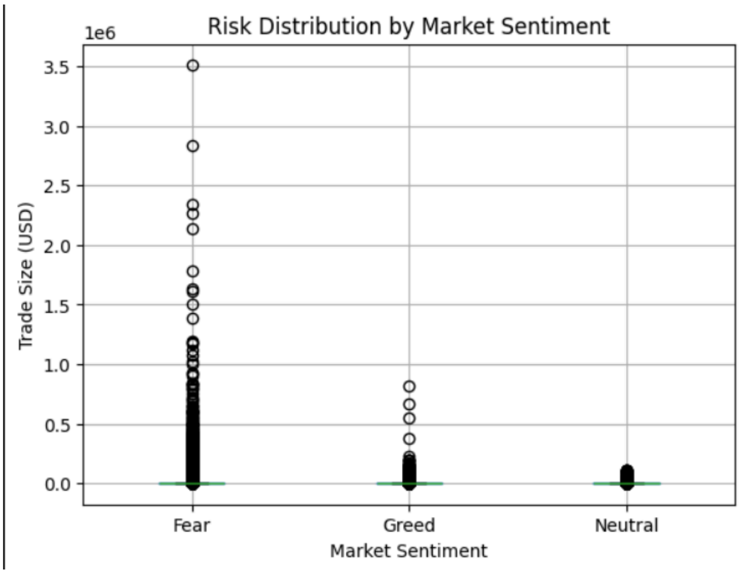
The total number of trades executed during Fear and Greed periods was analyzed.This step provides insight into **trader activity levels**, indicating whether traders are more active, cautious, or aggressive under different emotional market conditions.



5.2.a) Number of Trades vs Market Sentiment

5.3) Risk-Taking Behavior Analysis

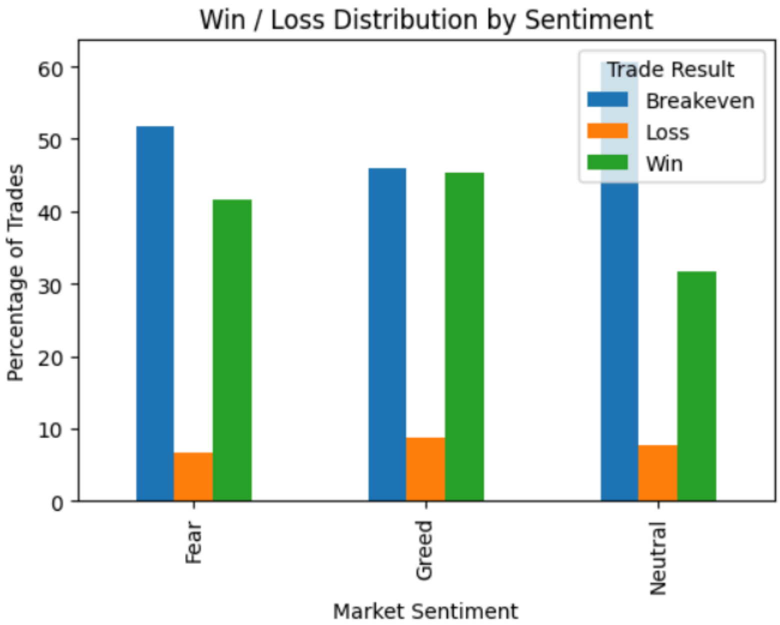
Risk-taking behavior was evaluated using **trade size in USD** as a proxy for risk exposure.By comparing average trade sizes across sentiments, this step identifies **when traders take larger positions and expose more capital to the market**.



5.3.a) Trade Size(USD) vs Market Sentiment

5.4) Winning vs Losing Trades Comparison

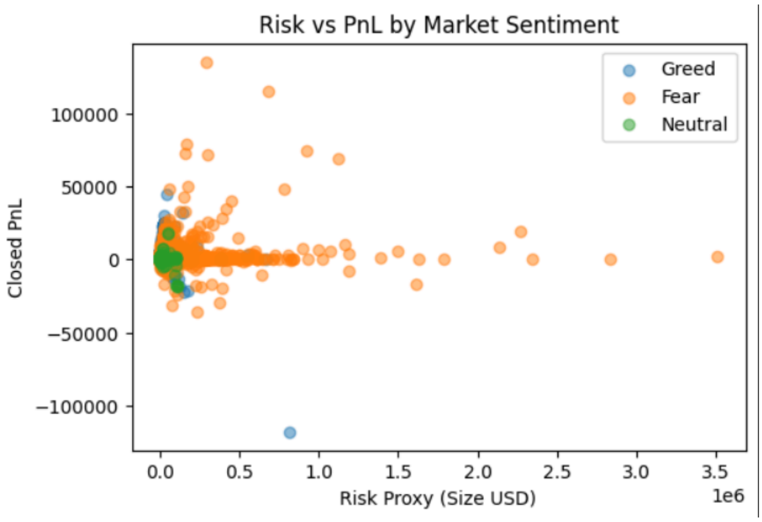
Trades were categorized as **Win**, **Loss**, or **Breakeven** based on realized PnL.The distribution of these outcomes was analyzed for Fear and Greed to determine **which sentiment leads to higher success rates and fewer losses**.



5.4.a) Percentage of Trades vs Market Sentiment

5.5) Trader-Level Behavioral Differences

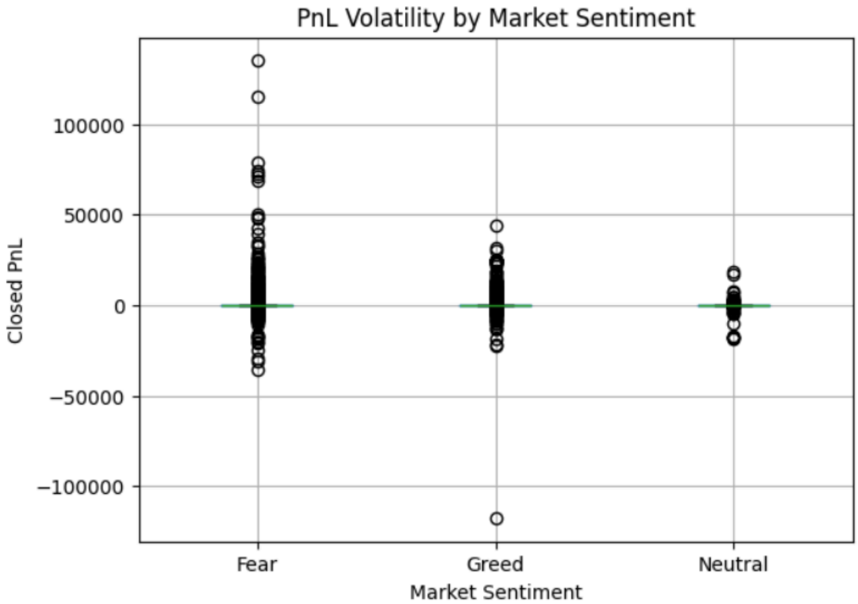
Trader behavior was analyzed at the individual level by comparing performance, risk exposure, and activity for the **same trader under different sentiments**.This step helps uncover **behavioral changes**, such as increased aggression or caution, driven by market emotions.



5.5.a) Closed PnL vs Risk Proxy (Size USD)

5.6) Stability and Volatility Analysis

To assess consistency in trader performance, volatility in profit and risk was measured under Fear and Greed conditions.This step evaluates whether trader outcomes are **stable or highly fluctuating** under the same sentiment, highlighting emotional instability or disciplined behavior.



5.6.a) Closed PnL vs Market Sentiment

6) Key Insights & Findings

The analysis reveals several important insights into how market sentiment influences trader behavior and performance.

6.1) Impact of Market Sentiment on Profitability

Trades executed during **Greed** market conditions show a **higher average closed PnL** compared to those executed during **Fear**. This indicates that traders tend to achieve better profitability when market sentiment is optimistic, although these gains are not always consistent.

6.2) Trading Activity Patterns

Trade frequency is noticeably higher during **Greed** periods, suggesting increased market participation and more aggressive trading behavior. In contrast, **Fear** periods are associated with reduced trading activity, indicating cautious or risk-averse behavior among traders.

6.3) Risk-Taking Behavior under Different Sentiments

Traders take **larger position sizes** during Greed sentiment, reflecting higher risk exposure. During Fear, traders generally reduce trade sizes, demonstrating a more conservative approach to risk management.

6.4) Win–Loss Dynamics

The proportion of winning trades is higher during **Greed** sentiment, while Fear periods exhibit a greater share of losing trades.This suggests that optimistic market conditions tend to align with improved trade outcomes, whereas fearful conditions often lead to suboptimal performance.

6.5) Behavioral Differences at Trader Level

Trader-level analysis shows that many traders change their behavior depending on market sentiment. The same trader often takes **higher risks and achieves higher profits during Greed**, while becoming more cautious or less profitable during Fear, highlighting the influence of emotions on decision-making.

6.6) Stability and Volatility of Outcomes

Although Greed is associated with higher profitability, it also shows **greater volatility in profit and risk**, indicating less stable outcomes. Fear periods exhibit lower volatility, suggesting more stable but lower-return trading behavior.

Overall, the findings confirm that market sentiment plays a significant role in shaping trader behavior, risk-taking, and performance, with Greed driving higher profits at the cost of increased instability, and Fear leading to more conservative but stable outcomes.

7) Practical Trading Strategy Insights

Based on the analysis of trader behavior under different market sentiments, several actionable insights can be derived to support smarter and more disciplined trading strategies.

7.1) Avoid Overexposure during Greed

Although Greed periods are associated with higher average profitability, they also show increased risk-taking and higher volatility. Traders should avoid excessively large position sizes during Greed and apply strict risk management rules to prevent large losses caused by emotional overconfidence.

7.2) Maintain Discipline during Fearful Markets

Fear-driven market conditions often lead to reduced activity and lower profitability.However, outcomes during Fear are generally more stable. Traders who maintain discipline and avoid panic-driven decisions may be able to identify selective opportunities without excessive risk exposure.

7.3) Focus on Position Sizing and Risk Control

The analysis highlights that risk exposure increases significantly during Greed.Implementing position-sizing strategies, such as limiting trade size or capital allocation per trade, can help balance potential returns with controlled risk.

7.4) Be Aware of Emotion-Driven Behavior

Trader-level analysis shows that many traders alter their behavior based on sentiment, often unconsciously. Recognizing emotional bias and following predefined trading rules can reduce impulsive decisions and improve long-term performance.

7.5) Prioritize Consistency over Short-Term Gains

While Greed may offer higher short-term profits, the associated volatility suggests inconsistent outcomes. Traders aiming for sustainable performance should prioritize consistency and stability rather than chasing high returns during emotionally charged market conditions.

By understanding how market sentiment influences profitability, risk-taking, and stability, traders can design strategies that mitigate emotional bias, manage risk effectively, and achieve more consistent trading outcomes.

8) Limitations and Future Scope

While the analysis provides meaningful insights into the relationship between market sentiment and trader behavior, certain limitations should be acknowledged.

8.1) Data Granularity Limitation

The market sentiment dataset is available at a **daily level**, whereas the trade dataset contains **trade-level timestamps**. As a result, all trades executed on the same day are associated with a single sentiment value, which may not fully capture intraday sentiment fluctuations.

8.2) Absence of Explicit Leverage Information

The dataset does not contain an explicit leverage column for each trade. To address this, trade size in USD was used as a proxy for risk exposure. While this provides a reasonable approximation, direct leverage data could improve risk analysis accuracy.

8.3) Market-Specific Scope

The analysis focuses solely on Bitcoin-related trading activity and sentiment. Results may differ across other cryptocurrencies or financial markets with different liquidity, volatility, and trader behavior patterns.

8.4) Future Improvements

The analysis can be extended further by:

- Incorporating **intraday sentiment data** for finer alignment with trades.
- Evaluating **risk-adjusted returns** to balance profit against risk.
- Segmenting traders based on experience or performance.
- Backtesting sentiment-aware trading strategies.

9) Conclusion

This analysis shows that **market sentiment has a strong impact on trader performance and behavior**. When the market is driven by **Greed**, traders trade more frequently, take larger risks, and on average earn higher profits. However, these profits are often unstable and come with higher volatility. During **Fear**, traders become more cautious, reduce trade size, and trade less often, resulting in lower but more stable outcomes.

The analysis also reveals hidden behavioral patterns: the **same trader behaves differently under Fear and Greed**, increasing risk and aggression during Greed while becoming conservative during Fear. This confirms that trading decisions are heavily influenced by emotions rather than consistent strategies.

These insights suggest that **smarter trading strategies should focus on controlling risk during Greed, maintaining discipline during Fear, and avoiding emotion-driven decisions**. By understanding sentiment-driven behavior, traders can improve consistency, manage risk better, and make more informed trading decisions.

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