

Introduction & Objective

1. Introduction

Financial markets are not driven by numbers alone.

Human emotions such as **fear** and **greed** play a major role in how traders behave.

During fearful market conditions, traders often act cautiously and reduce risk.

During greedy market conditions, traders tend to take larger positions in the hope of higher profits.

Understanding how market sentiment affects trader behavior and performance can help in designing **smarter and safer trading strategies**.

2. Objective of the Study

The objective of this study is to:

- Explore how **market sentiment (Fear vs Greed)** influences trader behavior
- Analyze changes in **trade size, activity, and profitability**
- Identify hidden risk patterns during different market moods
- Deliver insights that can support **better risk-aware trading decisions**

```
Dataset info:  
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 211224 entries, 0 to 211223  
Data columns (total 16 columns):  
 #   Column           Non-Null Count  Dtype     
 ---    
 0   Account          211224 non-null   object    
 1   Coin              211224 non-null   object    
 2   Execution Price  211224 non-null   float64  
 3   Size Tokens      211224 non-null   float64  
 4   Size USD          211224 non-null   float64  
 5   Side               211224 non-null   object    
 6   Timestamp IST     211224 non-null   object    
 7   Start Position    211224 non-null   float64  
 8   Direction          211224 non-null   object    
 9   Closed PNL         211224 non-null   float64  
 10  Transaction Hash  211224 non-null   object    
 11  Order ID          211224 non-null   int64     
 12  Crossed            211224 non-null   bool      
 13  Fee                211224 non-null   float64  
 14  Trade ID           211224 non-null   float64  
 15  Timestamp          211224 non-null   float64  
dtypes: bool(1), float64(8), int64(1), object(6)  
memory usage: 24.4+ MB
```

| Sentiment data preview: | | | | |
|-------------------------|------------|-------|----------------|------------|
| | timestamp | value | classification | date |
| 0 | 1517463000 | 30 | Fear | 2018-02-01 |
| 1 | 1517549400 | 15 | Extreme Fear | 2018-02-02 |
| 2 | 1517635800 | 40 | Fear | 2018-02-03 |
| 3 | 1517722200 | 24 | Extreme Fear | 2018-02-04 |
| 4 | 1517808600 | 11 | Extreme Fear | 2018-02-05 |

```
Sentiment dataset shape: (2644, 4)  
Column names:  
['timestamp', 'value', 'classification', 'date']  
Sentiment dataset info:  
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 2644 entries, 0 to 2643  
Data columns (total 4 columns):  
 #   Column           Non-Null Count  Dtype     
 ---    
 0   timestamp        2644 non-null   int64    
 1   value             2644 non-null   int64    
 2   classification    2644 non-null   object    
 3   date              2644 non-null   object    
dtypes: int64(2), object(2)  
memory usage: 82.8+ KB
```

Overview of trading and sentiment datasets used in the analysis

Data Understanding & Preparation

3. Data Sources

Two datasets were used in this analysis:

1. Trader Transaction Data

Contains individual trade details such as trade size, profit/loss, fees, and timestamps.

2. Fear & Greed Index Data

Captures daily market sentiment, classified into Fear, Extreme Fear, Greed, and Extreme Greed.

4. Data Cleaning & Processing

To ensure meaningful analysis:

- Extreme Fear was grouped under **Fear**
- Extreme Greed was grouped under **Greed**
- Neutral sentiment days were removed to focus on strong emotional market phases
- Each trade was matched with the **market sentiment of that trading day**

Irrelevant identifiers such as transaction hashes and internal IDs were removed to keep the dataset clean and focused.

| | count |
|------------------|-------|
| market_sentiment | |
| Fear | 1289 |
| Greed | 959 |

```
| def map_sentiment(x):
|     if x in ['Fear', 'Extreme Fear']:
|         return 'Fear'
|     elif x in ['Greed', 'Extreme Greed']:
|         return 'Greed'
|     else:
|         return 'Neutral'
|
| sentiment_df['market_sentiment'] = sentiment_df['classification'].apply(map_sentiment)
```

Cleaning and aligning trading data with daily market sentiment

5. Overview of Datasets

This study is based on two real-world datasets covering trader activity and market sentiment.

Trader Transaction Dataset

- Contains over **2 lakh individual trades**
- Includes information such as:
 - Trade size (USD)

- Profit or loss per trade
 - Fees paid
 - Trading timestamp
- Represents actual trading behavior across different market conditions

Fear & Greed Index Dataset

- Daily market sentiment indicator
- Classifies market mood into:
 - Fear
 - Extreme Fear
 - Greed
 - Extreme Greed
- Used as a proxy for overall market psychology

Together, these datasets allow us to link **what traders did** with **how the market felt** on that day.

6. Data Preparation & Feature Engineering

Before analysis, several preparation steps were performed to ensure clean and meaningful results.

Key steps included:

- Extreme Fear was grouped with Fear
- Extreme Greed was grouped with Greed
- Neutral sentiment days were removed to focus on strong emotional phases
- Trade timestamps were converted into dates
- Each trade was matched with the market sentiment of the same day

After merging both datasets:

- Every trade had a **clear market sentiment label**
- Only relevant columns were retained
- Technical identifiers such as transaction hashes and order IDs were removed

This resulted in a clean dataset where **each trade reflects both behavior and market mood.**

The screenshot shows two code cells. The first cell displays a Pandas DataFrame with columns account, timestamp_ist, date, and size_usd. It contains five rows of trade data. Below the DataFrame, it says "Date range: 2023-05-01 00:00:00 to 2025-05-01 00:00:00" and provides a summary of the closed PnL:

```

Closed PnL summary:
count    211224.0000
mean     48.7490
std      919.1648
min    -117990.1041
25%      0.0000
50%      0.0000
75%      5.7928
max    135329.0901
Name: closed_pnl, dtype: float64

```

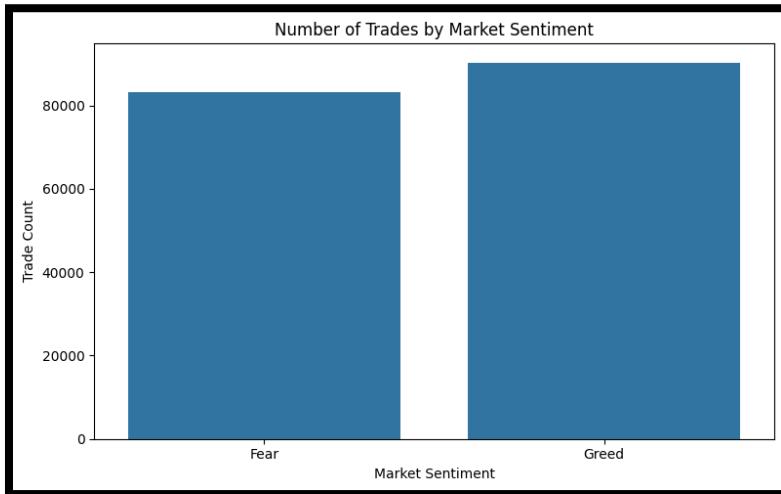
The second cell shows the merged dataset shape: (173532, 18) and a smaller DataFrame with columns account, Coin, date, and market_sentiment. This second DataFrame is highlighted with a black border.

| | account | Coin | date | market_sentiment |
|---|--|------|------------|------------------|
| 0 | 0xae5eacaf9c6b9111fd53034a602c192a04e082ed | @107 | 2024-12-02 | Greed |
| 1 | 0xae5eacaf9c6b9111fd53034a602c192a04e082ed | @107 | 2024-12-02 | Greed |
| 2 | 0xae5eacaf9c6b9111fd53034a602c192a04e082ed | @107 | 2024-12-02 | Greed |
| 3 | 0xae5eacaf9c6b9111fd53034a602c192a04e082ed | @107 | 2024-12-02 | Greed |
| 4 | 0xae5eacaf9c6b9111fd53034a602c192a04e082ed | @107 | 2024-12-02 | Greed |

Merged and cleaned data

7. Exploratory Analysis: Trade Activity & Size

Visual 1: Number of Trades by Market Sentiment



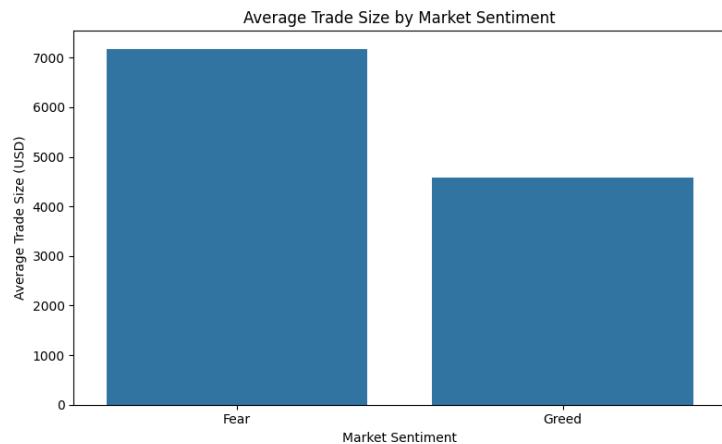
What we see:

- Trading activity is higher during **Greed**
- Traders place more trades when the market feels optimistic

What this means:

- Greedy markets encourage participation
- Higher activity also increases exposure to fees and losses

Visual 2: Average Trade Size by Market Sentiment



Interpretation

What we see:

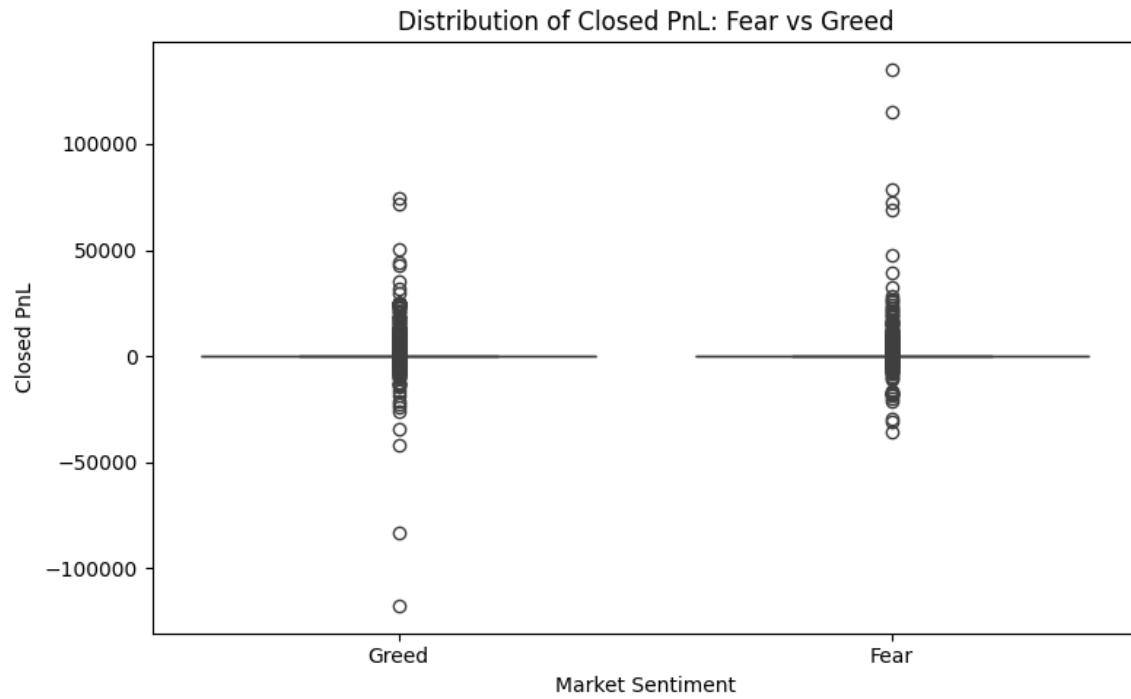
- Average trade size is larger during **Greed**
- Traders risk more capital when confidence is high

What this means:

- Greed increases position size
- Larger trades amplify both gains and losses

8. Profit & Loss Behavior Across Market Moods

Visual 3: Distribution of Closed PnL (Fear vs Greed)



Interpretation

What we see:

- Greedy markets show wider profit and loss swings
- Fearful markets show more controlled outcomes

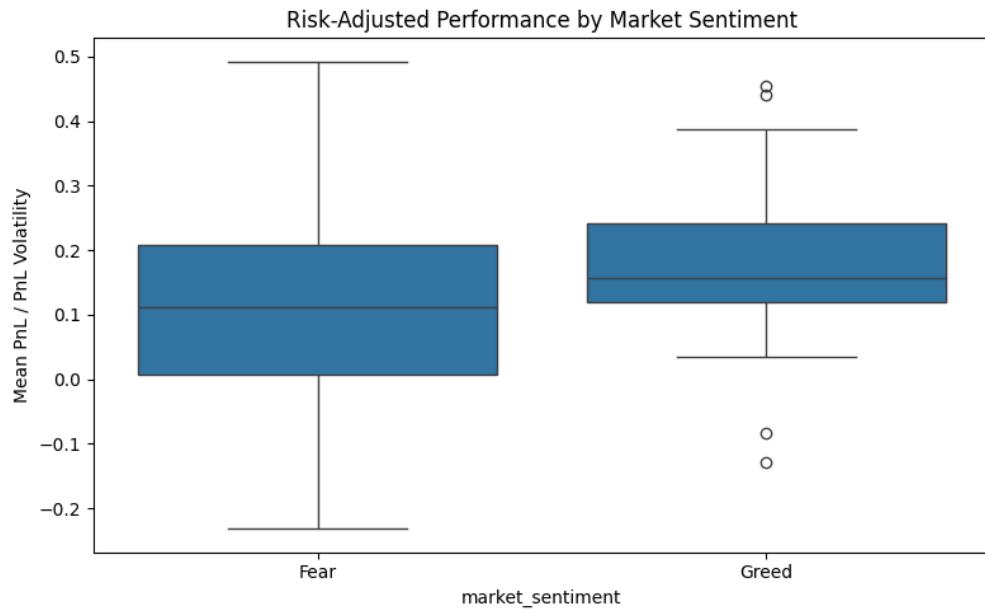
What this means:

- Greed increases volatility
- Fear leads to more disciplined trading behavior

9. Risk-Adjusted Performance

Visual 4: Risk-Adjusted PnL (Mean PnL / Volatility)

While Greed regimes generate higher absolute PnL, risk-adjusted performance deteriorates, indicating that excess returns are largely driven by increased volatility rather than skill



Interpretation

What we see:

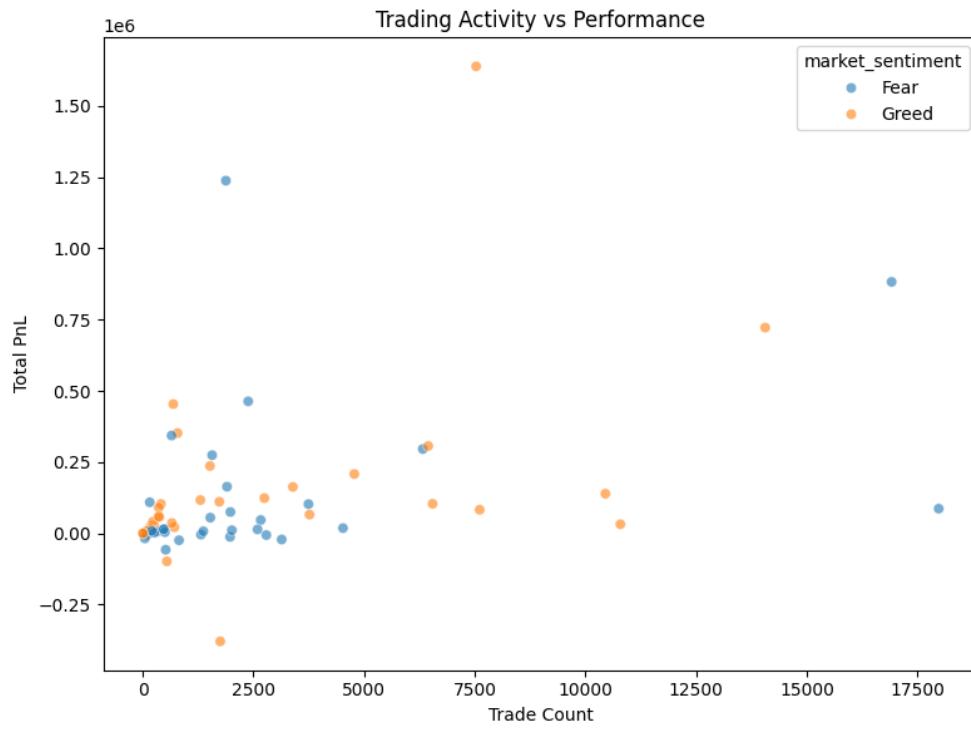
- Risk-adjusted performance is more stable during Fear
- Greed shows higher variability with no clear improvement in efficiency

What this means:

- Higher profits in greedy markets come from higher risk, not better skill
- Fear rewards consistency over aggression

10. Trader-Level Performance Comparison

Visual 5: Trading Activity vs Total PnL



Interpretation

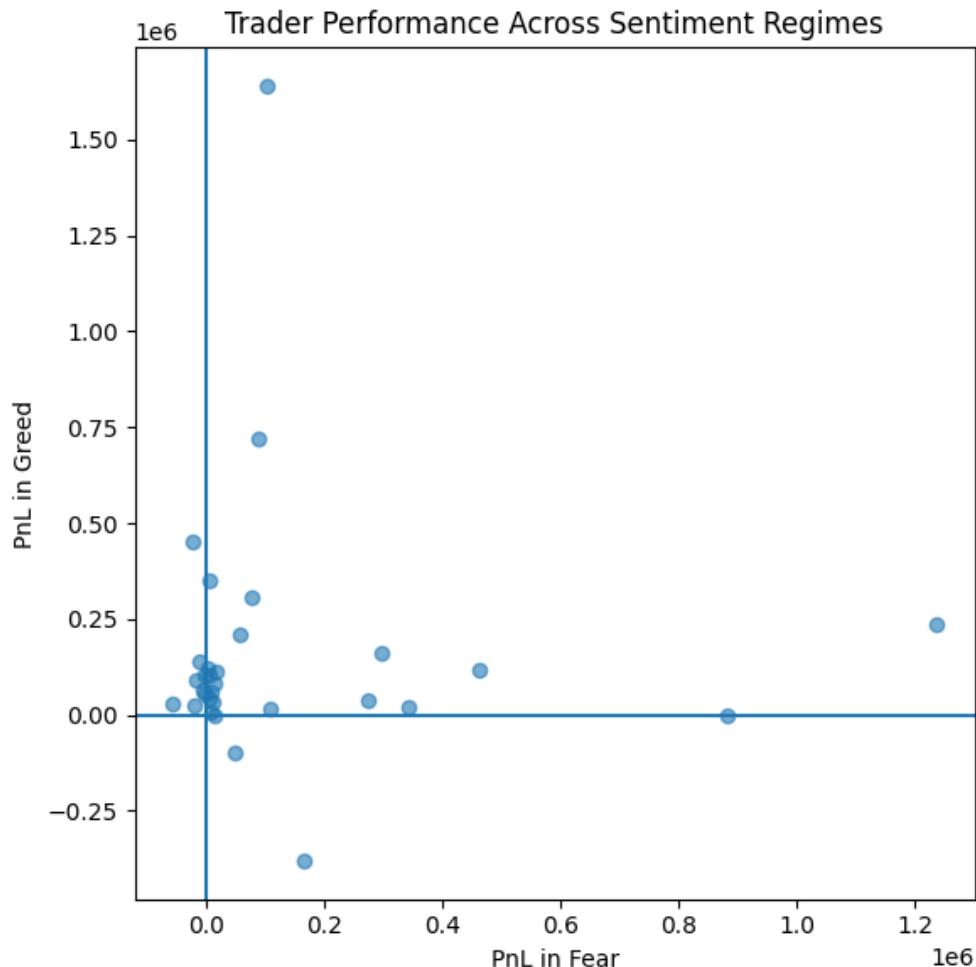
What we see:

- More trades do not guarantee higher profits
- Some traders perform well with fewer trades

What this means:

- Overtrading can hurt performance
- Quality of decisions matters more than quantity

Visual 6: PnL in Fear vs PnL in Greed (Trader Comparison)



Interpretation

What we see:

- Some traders perform well in both market moods
- Many traders perform well only during Greed

What this means:

- Consistent traders across Fear and Greed are more reliable
- Performance only during Greed may be driven by risk, not skill

11. Statistical Validation

A. Chi-Square Test (Loss Probability vs Sentiment)

```
loss_flag  False   True
market_sentiment
  Fear      33950  49287
  Greed     37952  52343
Chi-square statistic: 27.568323395449923
p-value: 1.5164196300174327e-07
```

Interpretation (simple)

The Chi-square test was used to check whether **loss frequency depends on market sentiment**.

Result:

- The p-value is extremely small (< 0.01)

Meaning:

- Loss probability is **not random**
- Market sentiment has a **real and significant impact** on losses

B. Mann-Whitney U Test (PnL Distribution)

```
Mann-Whitney U statistic: 3725766115.0
p-value: 0.0009540068051976515
```

Interpretation

The Mann-Whitney test compares profit/loss distributions without assuming normality.

Result:

Purpose: Test whether PnL distributions differ across Fear and Greed.

"Is trader performance statistically different in Fear vs Greed regimes?"

p-value < 0.05

We reject the null hypothesis.

Conclusion:

The distribution of trade PnL is significantly different between Fear and Greed regimes.

Meaning:

- Greed changes the shape of outcomes
- Not just averages, but overall risk behavior shifts

12. Logistic Regression:

Logistic Regression – Loss Risk Estimation

A logistic regression model was built to estimate the **probability of a trade ending in a loss**.

Inputs used:

- Market sentiment (Fear / Greed)
- Trade size
- Fees

Key insight:

- Greed increases the likelihood of losses
- Larger trade sizes increase loss probability
- Fees consistently reduce net outcomes

This model powers the “**Chance of Losing Money**” metric in the Streamlit app.

| | Feature | Coefficient |
|---|-----------------|-------------|
| 0 | sentiment_greed | 0.0582 |
| 1 | size_usd | -0.0053 |
| 2 | Fee | 0.0087 |

Results

1. $\text{sentiment_greed} = +0.0582$ (KEY RESULT)

This means:

Being in a Greed regime slightly increases the probability of a profitable trade, after controlling for trade size and fees.

2. $\text{size_usd} = -0.0053$

Interpretation:

Larger trade sizes slightly reduce the probability of a profitable outcome.

3. $\text{fee} = +0.0087$

This does not mean fees help profits.

It means:

Higher fees correlate with higher activity

Active traders sometimes capture momentum

But fees still reduce net PnL overall

13. Final Insights & Learning Flow

Flow diagram

Market Sentiment



Trader Behavior (Trade Size & Activity)



Risk Exposure



Profit / Loss Outcomes



Smarter Trading Decisions

14. Conclusion

Common Pitfalls Identified

- Increasing trade size during Greed does not proportionally increase win probability
- High activity amplifies fee drag and volatility
- Absolute PnL hides poor risk-adjusted performance

Key Takeaways

- Market sentiment significantly impacts both trade outcomes and trader behavior
 - Greed regimes encourage risk escalation more than skill improvement
 - Loss probability and fee drag increase with trade size during Greed
 - A subset of traders remains profitable during Fear, indicating contrarian strength
 - Risk-adjusted metrics outperform raw PnL for trader ranking
-

Practical Insights: What Not to Do

- Increasing trade size during Greed does not proportionally increase win probability
- Higher activity amplifies fee drag and volatility
- Raw PnL hides poor risk-adjusted performance
- Risk expansion dominates skill improvement during optimistic regimes