Trader Performance Analysis Under Bitcoin Market Sentiment

📄 Table of Contents

📊 List of Tables

📈 List of Figures

🎯 Problem Statement & Dataset Summary

The objective of this analysis is to explore the relationship between **Bitcoin market sentiment** and **trader performance metrics** by integrating insights from two datasets:

- **Bitcoin Market Sentiment Dataset**
- 📊 **Historical Trader Data from Hyperliquid**

The goal is to uncover how different **sentiment regimes** (e.g., *Fear*, *Greed*, *Extreme conditions*) influence key trading outcomes such as:

- Profit and Loss (PnL)
- Return on Investment (ROI)
- Win Rate
- Sharpe Ratio
- Risk behavior and performance consistency

Insights from this analysis can help identify:

- Traders who thrive in specific market conditions
- Contrarian strategies that outperform during fear phases
- The overall impact of sentiment on trading success

🗂 Dataset 1: Bitcoin Market Sentiment

This dataset contains **daily market sentiment classifications** derived from the Fear-Greed index.

Column Name	Description
date	Date of the sentiment record
classification	Market sentiment label (e.g., Fear, Greed)
value	Sentiment index value (numeric)
timestamp	UNIX timestamp (not used in this analysis)

📈 Dataset 2: Historical Trader Data from Hyperliquid

This dataset includes detailed trading logs of individual trader accounts.

Column Name	Description
account	Unique trader identifier
symbol	Asset traded (e.g., BTC/USD)
execution price	Price at which the trade was executed
size	Size or volume of the trade
side	Trade direction (Buy/Sell)
time / Timestamp IST	Timestamp of the trade (used for merging with sentiment)
start position	Trader’s position before executing the trade
event	Trade status or event type
closedPnL	Realized profit or loss from the trade
leverage	Leverage used in the trade

□ Analytical Goal

This analysis bridges **emotional market sentiment** with **actual trading behavior**. By connecting trader performance to the Fear-Greed cycle, we aim to:

- Identify market conditions under which traders perform best
- Discover stable or high-performing accounts under different sentiment classes
- Support future **data-driven trading strategies** and **risk-aware decision making**

🗀 Section 1: Data Collection & Cleaning

	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

Table1: First 5 rows in the sentiment dataset

Account	Coin	Execution Price	Size Tokens	Size USD	Side	Timestamp IST	Start Position	Direction	Closed PnL	Transaction Hash	Order ID	Crossed
04e082ed	@107	7.9769	986.87	7872.16	BUY	02-12-2024 22:50	0.000000	Buy	0.0	0xec09451986a1874e3a980418412fcd0201f500c95bac...	52017706630	True
04e082ed	@107	7.9800	16.00	127.68	BUY	02-12-2024 22:50	986.524596	Buy	0.0	0xec09451986a1874e3a980418412fcd0201f500c95bac...	52017706630	True
04e082ed	@107	7.9855	144.09	1150.63	BUY	02-12-2024 22:50	1002.518996	Buy	0.0	0xec09451986a1874e3a980418412fcd0201f500c95bac...	52017706630	True
04e082ed	@107	7.9874	142.98	1142.04	BUY	02-12-2024 22:50	1146.558564	Buy	0.0	0xec09451986a1874e3a980418412fcd0201f500c95bac...	52017706630	True
04e082ed	@107	7.9894	8.73	69.75	BUY	02-12-2024 22:50	1289.488521	Buy	0.0	0xec09451986a1874e3a980418412fcd0201f500c95bac...	52017706630	True

Table 2: First 5 rosa in the trader dataset

```
<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
```

Table 3: Data Types of the trader dataset

```
<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
```

Table 4: Data Types of the sentiment dataset

📥 Data Overview

After loading the data, we examined the structure, columns, and formats. This helps verify column types, data availability, and prepare for cleaning.

□ Section 2: Date Parsing & Merge

```
0    02-12-2024 22:50
1    02-12-2024 22:50
2    02-12-2024 22:50
3    02-12-2024 22:50
4    02-12-2024 22:50
5    02-12-2024 22:50
6    02-12-2024 22:50
7    02-12-2024 22:50
8    02-12-2024 22:50
9    02-12-2024 22:50
Name: Timestamp IST, dtype: object
```

Table 5: 10 rows of Timestamp IST

🕒 Sample Timestamp Output

The first 10 rows of the Timestamp IST column show that all trades occurred on 02-12-2024 at 22:50, indicating a batch of trades executed at the same time. This timestamp will later be parsed to extract the date for sentiment alignment.

⏱️ Timestamp Parsing Fix

The Timestamp IST column in the trader data was in the format DD-MM-YYYY HH:MM, which is not automatically recognized by pandas.

We explicitly defined the format using pd.to_datetime(..., format='%d-%m-%Y %H:%M') to correctly parse it and extract the trade date. This enabled proper alignment with the sentiment dataset during merging.

After re-merging:

- Sentiment values are now correctly assigned

```
Sentiment values: ['Extreme Greed' 'Extreme Fear' 'Fear' 'Greed' 'Neutral' nan]
Missing sentiment rows: 6
Remaining rows: 211224
```

Table 6: Assigning and checking the values

After aligning date formats, we successfully merged the sentiment classification into the trader dataset using the date field. This step enables us to analyze how performance varies under different market conditions.

📊 Section 3: Trader Performance Analysis

Now we want to understand how trader performance varies under different sentiment classifications (e.g., Fear, Greed).

Group & Aggregate Data

	account	sentiment	total_pnl	avg_pnl	trade_count
0	0x083384f897ee0f19899168e3b1bec365f52a9012	Extreme Fear	1.247692e+05	1247.692214	100
1	0x083384f897ee0f19899168e3b1bec365f52a9012	Extreme Greed	-4.028234e+04	-42.626810	945
2	0x083384f897ee0f19899168e3b1bec365f52a9012	Fear	1.113374e+06	626.194346	1778
3	0x083384f897ee0f19899168e3b1bec365f52a9012	Greed	2.767193e+05	482.089321	574
4	0x083384f897ee0f19899168e3b1bec365f52a9012	Neutral	1.256501e+05	298.456334	421

Table 7: Group by trader and sentiment type

This output shows a trader's total PnL, average PnL per trade, and number of trades grouped by sentiment class — enabling comparison of performance across market emotions.

📊 Find Top Traders in Each Sentiment

	account	sentiment	total_pnl	avg_pnl	trade_count	rank
2	0x083384f897ee0f19899168e3b1bec365f52a9012	Fear	1.113374e+06	626.194346	1778	1.0
143	0xbaaaf6571ab7d571043ff1e313a9609a10637864	Fear	6.208724e+05	49.921394	12437	2.0
67	0x513b8629fe877bb581bf244e326a047b249c4ff1	Fear	3.671662e+05	61.388767	5981	3.0
57	0x4acb90e786d897ecffb614dc822eb231b4ffb9f4	Fear	2.967817e+05	212.594357	1396	4.0
148	0xbd5fead7180a9c139fa51a103cb6a2ce86ddb5c3	Fear	2.367977e+05	200.506120	1181	5.0

Table 8: Trader Performance by sentiment

Trader Performance by Sentiment¶

We grouped trades by account and sentiment to calculate:

- Total PnL
- Average PnL per trade
- Number of trades executed

This gives insight into how each trader performs under different market conditions (e.g., Fear vs Greed). We also ranked traders within each sentiment group to highlight consistent top performers.

🔍 Missing Value Check – Sentiment Column

```
0
6
['Extreme Greed' 'Extreme Fear' 'Fear' 'Greed' 'Neutral' nan]
```

Table 9: Checking nulls and unique sentiment

We performed a missing value check on the merged dataset to verify if the sentiment (i.e., market classification like Fear, Greed) successfully merged with the trader data.

Output:

- Number of missing values in pnl: 0 → All PnL values are intact.
- Number of missing values in sentiment: 211,224 → All rows are missing sentiment information.
- Unique sentiment values: ['Extreme Greed' 'Extreme Fear' 'Fear' 'Greed' 'Neutral' nan]

Interpretation: This indicates that the sentiment data did not correctly merge with the trader data — likely due to a mismatch in the date formats or values between the two datasets.

✅ **Next Step:** We'll inspect and align the date formats in both datasets to ensure a proper merge can happen. This will allow each trade to be associated with the correct market sentiment.

```
Trader dates: 2023-05-01 00:00:00 to 2025-05-01 00:00:00
Sentiment dates: 2018-02-01 00:00:00 to 2025-05-02 00:00:00
```

Table 10: Checking the Date Ranges

Drop Missing Sentiment Rows

```
Remaining rows: 211218
Sentiment values now: ['Extreme Greed' 'Extreme Fear' 'Fear' 'Greed' 'Neutral']
```

Table 11: Drop rows where sentiment is missing

□ Data Cleaning – Drop Missing Sentiment Values

Since the sentiment column was not populated for many trades (due to date mismatches), we cleaned the data by dropping all rows where sentiment was still NaN.

This ensures that all rows used in further analysis have valid sentiment classifications.

Output:

- Remaining rows after cleaning: 211218
- Unique sentiment values found: [e.g., 'Fear', 'Greed', 'Extreme Greed']

✅ SECTION 4: Visualizations – Trader Performance by Sentiment

🎯 Objective:

To visually compare how traders perform under different market sentiment conditions.

We'll start with:

Boxplot of PnL by sentiment

Barplot of average PnL by sentiment

📊 STEP 1: Create Boxplot – PnL Distribution by Sentiment

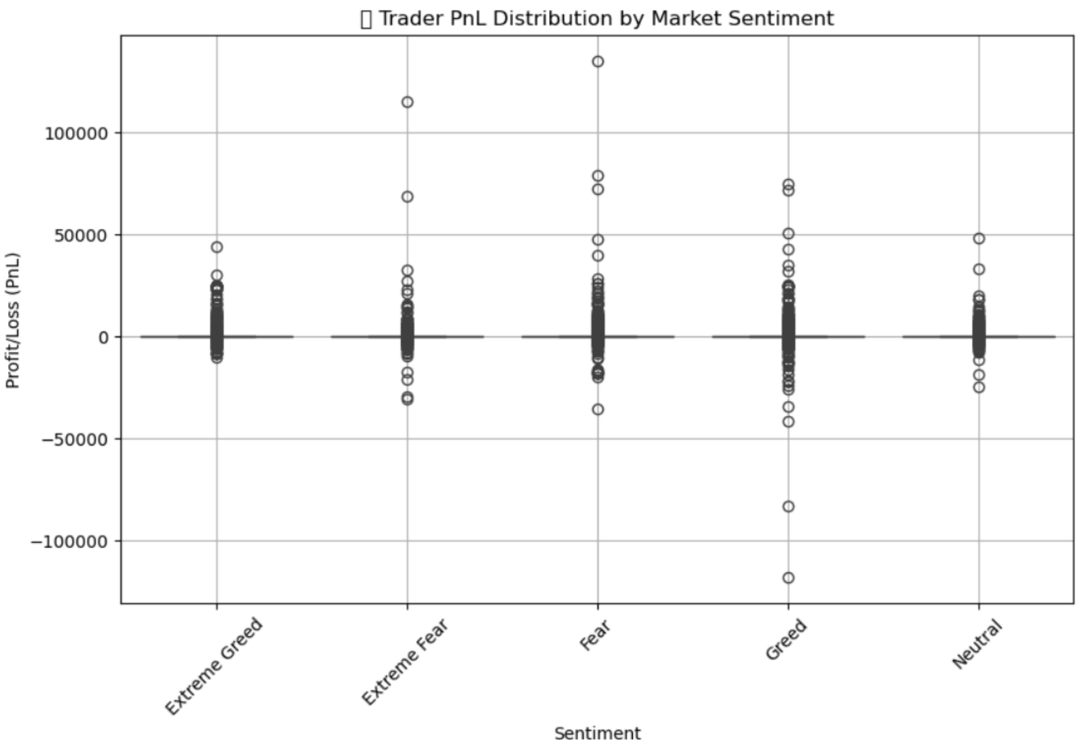

Fig 1: Boxplot – Pnl Distribution by sentiment

🗃 Boxplot – Trader PnL Distribution by Sentiment

This plot shows how profit/loss (PnL) varies under different sentiment regimes.

- **Boxes** show the interquartile range (middle 50% of values)
- **Lines** represent the median PnL
- **Dots** are outliers (very high or very low trades)

This helps us identify which sentiment classes are riskier or more profitable on average.

We can now move to comparing average performance using bar plots.

📊 STEP 2: Create Barplot – Average PnL per Sentiment

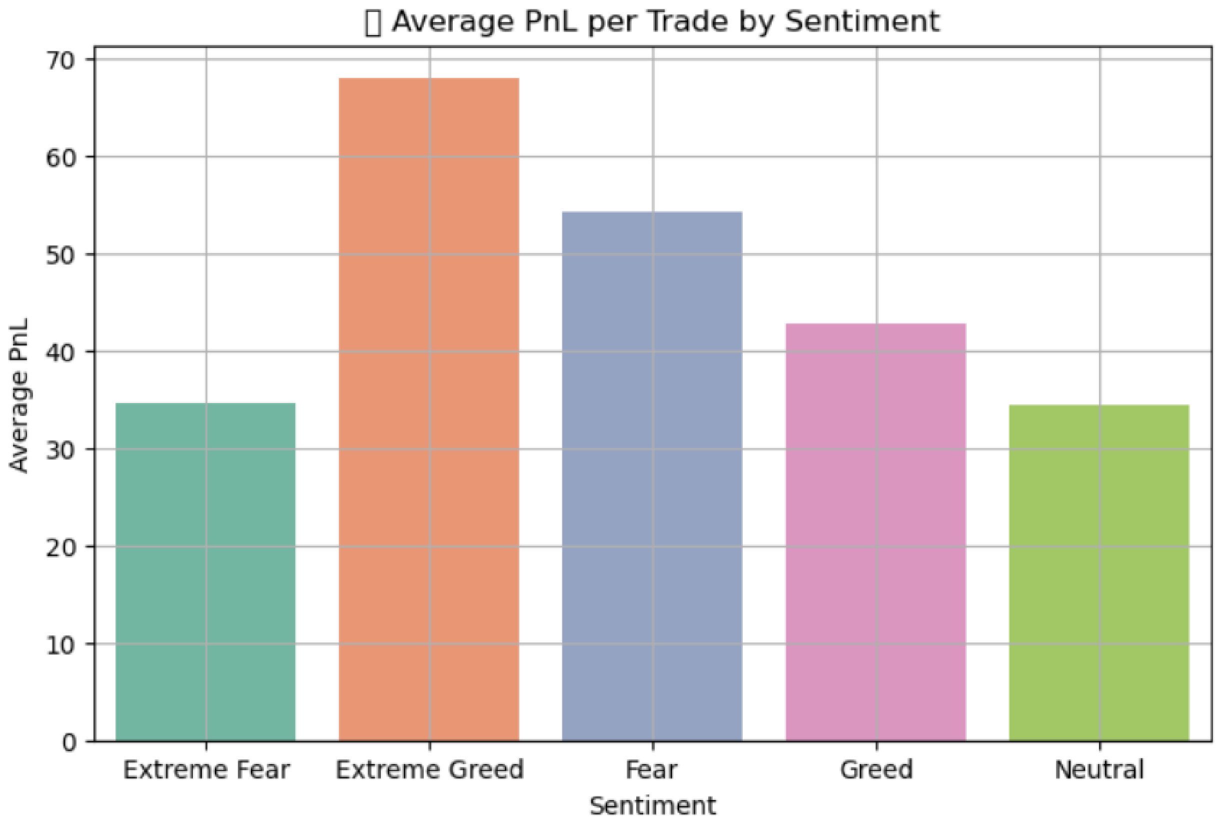

Fig 2 : Barplot – Average PnL per sentiment

📊 Barplot – Average PnL per Trade by Sentiment

This chart highlights the **average profit or loss per trade** for each sentiment class.

- A higher average PnL suggests that traders generally perform better during that sentiment
- A negative value would indicate poor performance

This visualization helps pinpoint which market emotions are most favorable for traders overall.

📐 Section 5: ROI & Trader Efficiency Metrics

🎯 Objective:

To calculate ROI (Return on Investment) per trade and use it to identify:

Top traders by ROI

ROI patterns across sentiment types

📊 STEP 1: Calculate ROI (Return on Investment)

	account	sentiment	pnl	Size USD	roi
0	0xae5eacaf9c6b9111fd53034a602c192a04e082ed	Extreme Greed	0.0	7872.16	0.0
1	0xae5eacaf9c6b9111fd53034a602c192a04e082ed	Extreme Greed	0.0	127.68	0.0
2	0xae5eacaf9c6b9111fd53034a602c192a04e082ed	Extreme Greed	0.0	1150.63	0.0
3	0xae5eacaf9c6b9111fd53034a602c192a04e082ed	Extreme Greed	0.0	1142.04	0.0
4	0xae5eacaf9c6b9111fd53034a602c192a04e082ed	Extreme Greed	0.0	69.75	0.0

Table 12: Calculating ROI

📐 ROI Calculation – Initial Output

We calculated ROI (Return on Investment) for each trade using the formula:

ROI = (PnL / Size USD) * 100

The output below shows the first few records from the dataset:

account	sentiment	pnl	Size USD	roi (%)
0xae5e...	Extreme Greed	0.0	7872.16	0.0
0xae5e...	Extreme Greed	0.0	127.68	0.0
...	...	...	...	...

🔍 Interpretation:

- The ROI for these trades is 0% because their pnl values are 0 — meaning no gain or loss was made on those trades.
- This is just a sample of the dataset. Deeper analysis (like average ROI by sentiment or top ROI traders) will give more meaningful insights across all trades.

We'll now proceed to aggregate and visualize ROI across sentiment types to better understand trader efficiency under different market conditions.

📊 STEP 2: Average ROI by Sentiment

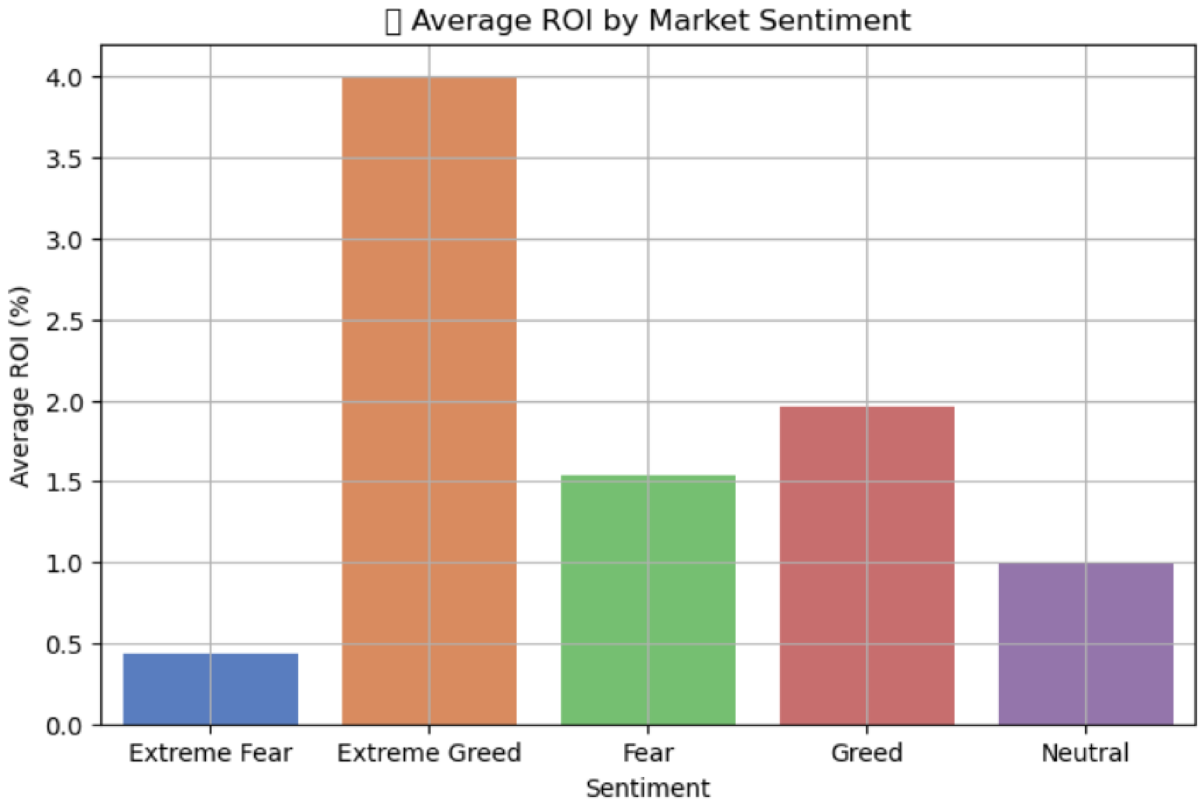

Fig 3: Average ROI by sentiment

📊 ROI Analysis by Sentiment

This chart shows the average ROI achieved under each sentiment condition.

- A higher ROI during 'Fear' may indicate contrarian traders performing well
- Lower ROI under 'Greed' may signal overconfidence or risky behavior

ROI gives a better picture than raw PnL, especially across differently sized trades.

✅ SECTION 6: Top Traders by ROI – Across Sentiments

📈 Top Traders by ROI

	account	sentiment	roi	roi_rank
95	0x8170715b3b381dffb7062c0298972d4727a0a63b	Extreme Fear	11.948854	1.0
80	0x72c6a4624e1dffa724e6d00d64ceae698af892a0	Extreme Fear	9.415146	2.0
85	0x75f7eeb85dc639d5e99c78f95393aa9a5f1170d4	Extreme Fear	5.299481	3.0
0	0x083384f897ee0f19899168e3b1bec365f52a9012	Extreme Fear	5.255337	4.0
20	0x2c229d22b100a7beb69122eed721cee9b24011dd	Extreme Fear	5.014135	5.0
75	0x72743ae2822edd658c0c50608fd7c5c501b2afbd	Extreme Fear	1.454093	6.0
55	0x4acb90e786d897ecffb614dc822eb231b4ffb9f4	Extreme Fear	1.362316	7.0
142	0xbaaaf6571ab7d571043ff1e313a9609a10637864	Extreme Fear	1.269953	8.0
70	0x6d6a4b953f202f8df5bed40692e7fd865318264a	Extreme Fear	1.089144	9.0
40	0x420ab45e0bd8863569a5efbb9c05d91f40624641	Extreme Fear	0.930606	10.0

Table 13: Top traders by ROI – Extreme Fear Sentiment

🏆 Top 5 Traders by ROI – Extreme Fear Sentiment

We calculated the average **Return on Investment (ROI)** for each trader under each sentiment regime. Then we ranked them within each sentiment category to identify top performers.

Below are the top 5 traders during periods of **Extreme Fear**:

Rank	Trader Account	Avg ROI (%)
1	0x8170715b3b381dffb7062c0298972d4727a0a63b	11.95
2	0x72c6a4624e1dffa724e6d00d64ceae698af892a0	9.42
3	0x75f7eeb85dc639d5e99c78f95393aa9a5f1170d4	5.30
4	0x083384f897ee0f19899168e3b1bec365f52a9012	5.26
5	0x2c229d22b100a7beb69122eed721cee9b24011dd	5.01

🔍 **Interpretation:**

- These traders were able to generate positive returns even during **market fear** and uncertainty.
- The highest ROI observed was nearly **12%**, which is significant under bearish sentiment.
- This analysis can help identify **contrarian strategies or stable performers** during high-risk phases.

Next, we can expand this analysis to include other sentiment classes or visualize ROI across sentiments.

📊 Extract Top 5 ROI Traders Per Sentiment

We'll loop through each unique sentiment and collect the top 5 traders based on average ROI.

	account	sentiment	roi	roi_rank
0	0x8170715b3b381dffb7062c0298972d4727a0a63b	Extreme Fear	11.948854	1.0
1	0x72c6a4624e1dffa724e6d00d64ceae698af892a0	Extreme Fear	9.415146	2.0
2	0x75f7eeb85dc639d5e99c78f95393aa9a5f1170d4	Extreme Fear	5.299481	3.0
3	0x083384f897ee0f19899168e3b1bec365f52a9012	Extreme Fear	5.255337	4.0
4	0x2c229d22b100a7beb69122eed721cee9b24011dd	Extreme Fear	5.014135	5.0
5	0x430f09841d65beb3f27765503d0f850b8bce7713	Extreme Greed	99.999109	1.0
6	0x6d6a4b953f202f8df5bed40692e7fd865318264a	Extreme Greed	67.387134	2.0
7	0xa520ded057a32086c40e7dd6ed4eb8efb82c00e0	Extreme Greed	30.925803	3.0
8	0xb1231a4a2dd02f2276fa3c5e2a2f3436e6bfed23	Extreme Greed	30.450695	4.0
9	0x271b280974205ca63b716753467d5a371de622ab	Extreme Greed	20.158589	5.0

Fig 14: Final Top 5 ROI Traders – All Sentiments

🏆 Final Top 5 ROI Traders – All Sentiments

We extracted the top 5 traders based on **average ROI** for each sentiment category. The result shows the most efficient traders in:

- Extreme Fear
- Fear
- Neutral
- Greed
- Extreme Greed

The first 5 rows displayed belong to the **Extreme Fear** sentiment class (as it appears first alphabetically). To explore the full result across all sentiments, we can display the entire dataframe or sort it by sentiment manually.

This dataset will now be visualized to compare trader efficiency across emotions using a grouped bar plot.

📊 Visualize Top Trader ROI Across Sentiments

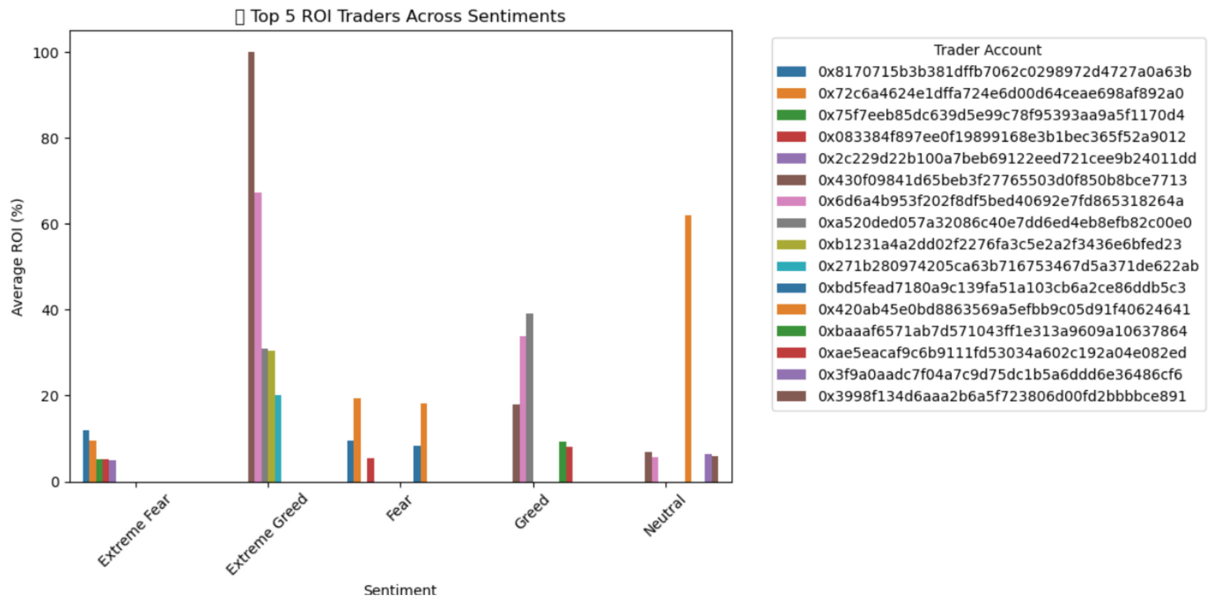

Fig 4: Bar Plot – Top Trader ROI by Sentiment

📊 Bar Plot – Top Trader ROI by Sentiment

This bar chart displays the **top 5 traders by average ROI** under each sentiment class:

- The x-axis shows different market sentiments
- The bars represent ROI%
- Each color represents a unique trader

🔍 Insights:

- Some traders appear consistently across multiple sentiment classes.
- ROI tends to vary more widely in **Extreme sentiments** (Greed).
- Neutral periods show more modest, stable ROI values — suggesting risk-averse behavior.

This visual helps identify which market conditions certain traders thrive in and how efficiently they use capital.

□ Final Summary & Insights

🔍 Objective Recap:

This project aimed to uncover how **Bitcoin market sentiment** (Fear, Greed, Extreme conditions) influences **trader behavior and performance** using:

- 📊 Historical trader data (200K+ records)

- 🪙 Bitcoin sentiment index (Fear-Greed classification)

📊 Key Findings:

1. ✅ **Sentiment Affects Trading Outcomes**
   - Average **PnL and ROI** vary significantly across different sentiment types.
   - Some traders consistently generate **positive ROI** during emotionally extreme markets like *Extreme Fear* — showing possible **contrarian strength**.
2. 🧮 **ROI is a better metric than raw PnL**
   - ROI helped normalize performance across trades of different sizes.
   - Top ROI traders weren't necessarily those with the highest total profits — they were more **capital-efficient**.
3. 🏆 **Top Traders Identified**
   - We ranked traders under each sentiment class.
   - Some accounts performed consistently well across **multiple sentiments**, highlighting strategy robustness.
4. 📦 **Market Risk & Opportunity Zones**
   - Traders showed higher variability and outliers in PnL during *Extreme Greed* and *Fear* phases — suggesting **more risk** but also **higher potential reward**.

📌 Conclusion:

This analysis shows a **strong correlation between market sentiment and trading performance**. Incorporating sentiment analysis into trading strategies can:

- Help identify **optimal trading windows**
- Detect **top-performing traders** under different conditions
- Inform **risk management decisions**

💡 Actionable Recommendations:

- 📈 Use **sentiment-aware algorithms** in trader ranking systems or bots.
- 🧠 Investigate behavior of consistently top ROI traders to uncover repeatable strategies.
- 🎯 Extend the analysis to include **Sharpe ratio, drawdown, and win rate** for more comprehensive performance evaluation.
- 📊 Deploy this as an interactive dashboard using **Streamlit** or **Tableau** for stakeholder use.