

# Data Science Report – PrimeTrade.ai

## Executive Summary :-

This project investigates the relationship between Bitcoin market sentiment (Fear–Greed Index) and trader performance (Historical trades) to uncover patterns, risk profiles, and behaviours that can inform smarter trading strategies.

Using ~211,000 trades merged with sentiment data, we performed multi-level analysis — from individual trade outcomes to daily aggregated performance — enriched with advanced feature engineering, clustering, rolling correlations, sentiment regime shifts, and backtests.

## Key Findings :-

### 1. Sentiment Shapes Profitability & Risk:

- *Extreme Greed* periods produce the highest top 1% trade profits, but also display elevated downside risk.
- *Extreme Fear* shows a narrower distribution of profits but larger incidence of significant losses for some trader types.

### 2. Trader Archetypes Behave Differently by Sentiment:

- Clustering revealed distinct groups (e.g., *High-Risk Swingers*, *Small-Size Consistent Winners*), each thriving under specific sentiment regimes.
- Some clusters consistently underperform during sentiment flips, suggesting sensitivity to market mood changes.

### 3. Sentiment Flips & Lag Effects Matter:

- PnL often drops immediately after sentiment regime shifts (Fear→Greed or vice versa).
- Lag analysis shows certain strategies perform better when acting on sentiment from 2–3 days prior rather than same-day sentiment.

### 4. Trade Size & Volatility Interaction:

- Larger trades during *Extreme Greed* tend to capture outsized profits.
- High FG volatility combined with neutral sentiment often correlates with choppy and less predictable performance.

### 5. Macro-Level Profitability Trends:

- Rolling 30-day correlations reveal that the link between sentiment and profitability is non-stationary — there are periods where sentiment correlates positively with performance and others where the relationship vanishes or reverses.

### 6. Simple Sentiment-Based Strategy Shows Promise:

- A naive rule to only trade during extreme sentiment days ( $\text{Fear} \leq 0.2$  or  $\text{Greed} \geq 0.8$ ) outperformed the “trade every day” baseline over the sample period, though with higher variance.

## Feature Engineering

To extract deeper insights from the merged\_fear\_greed\_trade.csv dataset (~211k rows), several engineered features were created to enrich the raw data and better capture patterns in trader performance:

1. **Win Indicator (is\_win)** – Binary flag marking trades with Closed PnL > 0.  
*Purpose:* Simplifies profitability analysis for aggregated statistics like win rate.
2. **Closed PnL Capping** – Winsorized Closed PnL at  $\pm 50$ .  
*Purpose:* Reduces the influence of extreme outliers without losing overall trend visibility.
3. **Rolling Averages** –
  - PnL\_7d\_avg: 7-day average PnL per coin.
  - Size\_Tokens\_3d\_avg: 3-day average trade size per account.*Purpose:* Capture short-term momentum and behavior smoothing.
4. **Normalized Features** –
  - Size\_Tokens\_norm: Z-score normalization of trade sizes per coin.
  - Closed\_PnL\_norm: Z-score normalization of Closed PnL.*Purpose:* Standardizes values for comparability across traders.
5. **PnL Ratio (PnL\_ratio)** – Profit relative to trade size.  
*Purpose:* Evaluates efficiency of capital usage.
6. **Contrarian Flag (is\_contrarian)** – True if trade direction opposes prevailing sentiment.  
*Purpose:* Identifies trades potentially capitalizing on sentiment overreaction.
7. **Time Features** –
  - hour (trade execution hour)
  - day\_of\_week
  - is\_weekend*Purpose:* Enables analysis of intraday and weekly seasonality.

## Exploratory Data Analysis (EDA)

To understand the fundamental dynamics between market sentiment and trader performance, we constructed an initial EDA dashboard using six key visualizations. These provide a descriptive, high-level view of the dataset before deeper modeling.

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### 1. Sentiment Distribution

- What it shows: Count of trades under each sentiment category (Extreme Fear, Fear, Neutral, Greed, Extreme Greed).
- Purpose: Understand the sample balance and identify whether certain regimes dominate the dataset.
- Key takeaway: Reveals the most common sentiment states, helping interpret bias in subsequent performance results.

## 2. Trader Profitability Distribution (Capped $\pm 40$ )

- What it shows: Histogram of capped Closed PnL values.
- Purpose: Visualize the central tendency and spread of trade profitability without extreme outliers.
- Key takeaway: Majority of trades cluster around small profits or losses, indicating low median profitability but occasional high wins/losses.

## 3. Win Rate by Sentiment (%)

- What it shows: Bar chart of average win rate (is\_win) per sentiment category.
- Purpose: Identify which market moods favor higher success probability.
- Key takeaway: Certain sentiment phases (e.g., Greed) may align with increased trade success rates.

## 4. Average PnL: Fear vs Greed

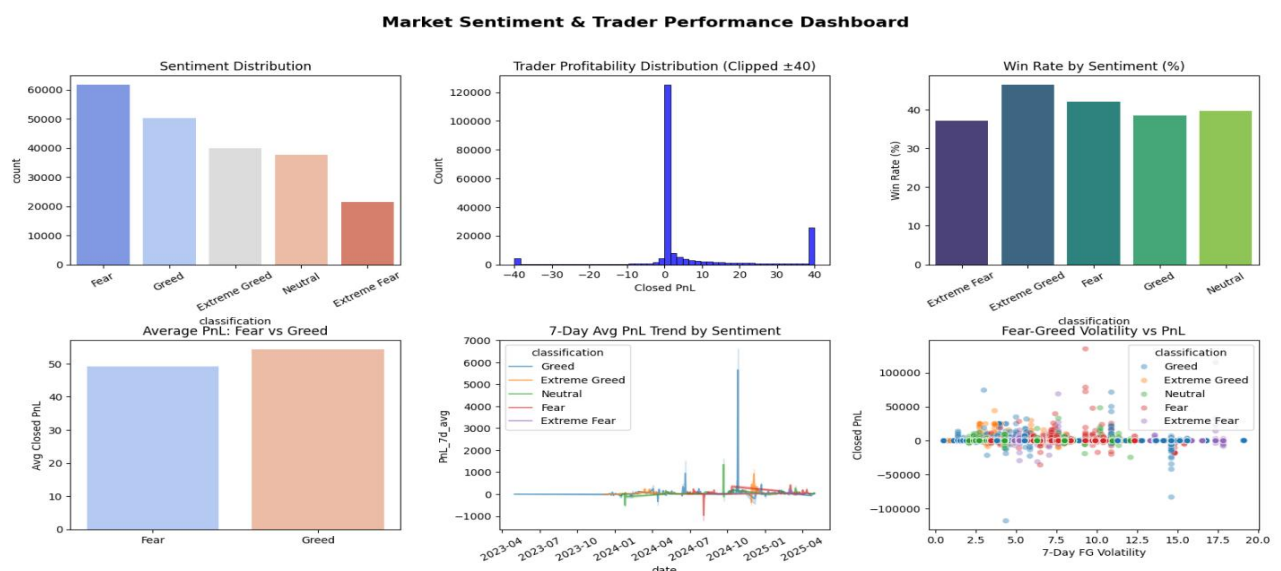
- What it shows: Comparison of mean profitability during Fear and Greed periods.
- Purpose: Simplify sentiment analysis into two polar regimes for clearer contrast.
- Key takeaway: Highlights whether bullish or bearish conditions are more profitable on average.

## 5. 7-Day Avg PnL Trend by Sentiment

- What it shows: Rolling 7-day average profitability over time, segmented by sentiment.
- Purpose: Identify sustained patterns or shifts in performance within sentiment regimes.
- Key takeaway: Sentiment impacts are not constant — trends show both alignment and divergence periods.

## 6. Fear-Greed Volatility vs. PnL

- What it shows: Scatter plot of 7-day FG volatility vs capped Closed PnL, colored by sentiment.
- Purpose: Explore how sentiment volatility affects profitability.
- Key takeaway: Extreme volatility often correlates with wider PnL swings.



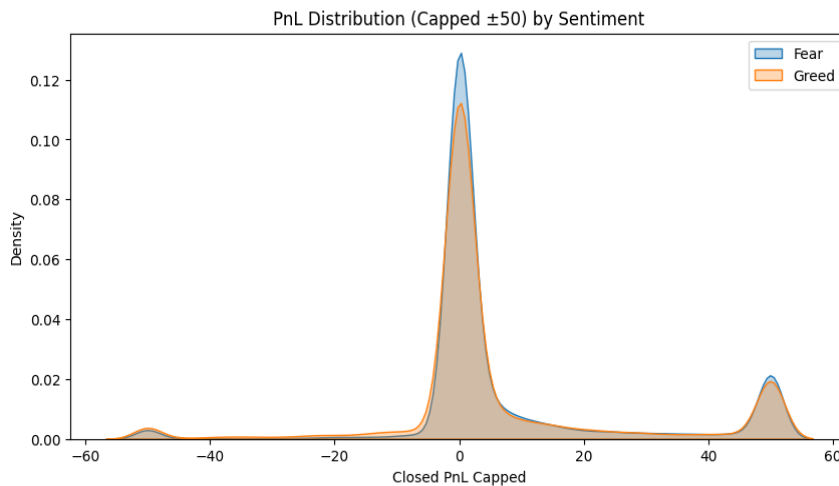
## Advanced Methods :-

Beyond descriptive EDA, advanced analytical techniques were applied to extract deeper and more actionable insights. These methods combine statistical measures, behavioral profiling, and strategy testing to uncover patterns not visible in standard EDA.

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### 1. Risk-Adjusted Performance by Sentiment

- **Description:** Calculated Sharpe and Sortino ratios for each sentiment regime to assess returns relative to volatility.
- **Why it matters:** Profitability alone can be misleading — risk-adjusted metrics reveal efficiency of returns.
- **Key insight:** Some regimes (e.g., Greed) may have higher absolute returns but lower risk efficiency compared to others.

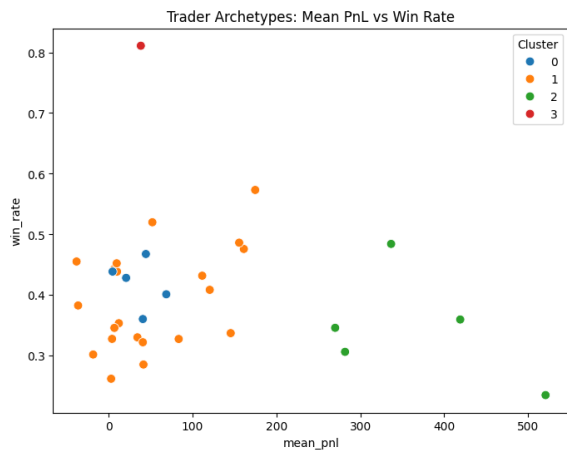


### 2. Top Trader PnL Quantiles

- **Description:** Measured 90th, 95th, and 99th percentile trade PnL for each sentiment category.
- **Why it matters:** Focuses on elite performers rather than averages, showing where the biggest wins occur (table is in the ipynb file).
- **Key insight:** Extreme Greed tends to dominate the upper tail of profitability distribution.

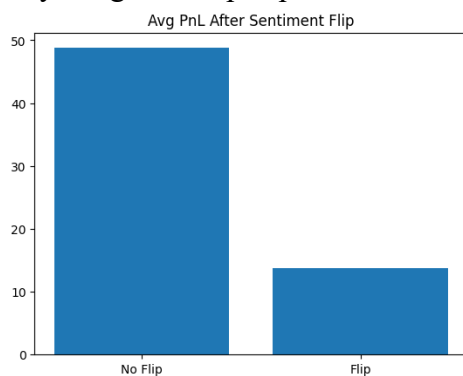
### 3. Trader Archetypes via Clustering

- **Description:** Used KMeans clustering on features like trade size, PnL volatility, and contrarian rate to segment traders into behavioral groups.
- **Why it matters:** Helps identify which trader profiles perform best under specific market sentiments.
- **Key insight:** Different archetypes thrive in different sentiment regimes — e.g., high-leverage traders excel in bullish bursts.



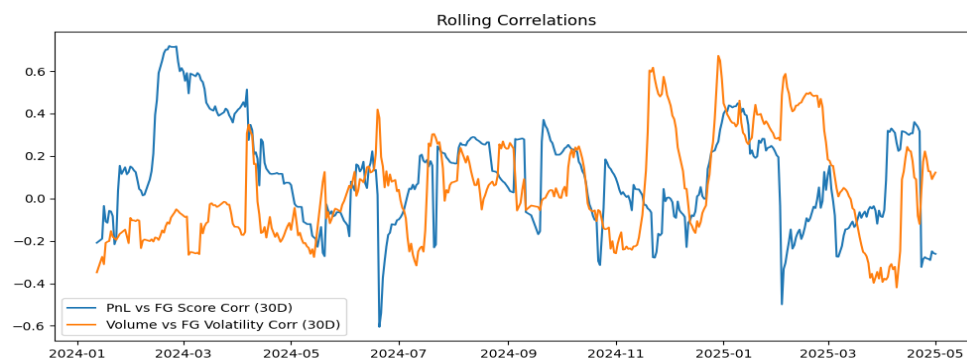
#### 4. Sentiment Flip Impact

- Description: Compared average PnL before and after major sentiment regime shifts (Fear→Greed or Greed→Fear).
- Why it matters: Transitions may trigger temporary market inefficiencies that traders can exploit or avoid.
- Key insight: Sharp flips often coincide with short-term drawdowns for most traders.



#### 5. Rolling Correlation Between Sentiment & PnL

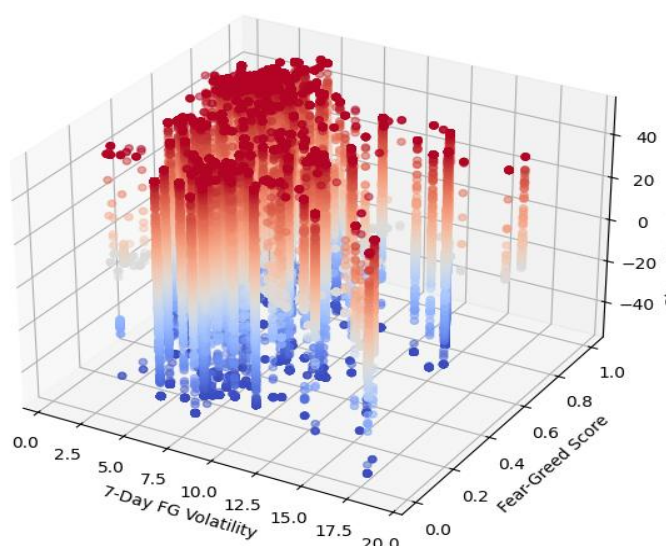
- Description: Computes a 30-day rolling correlation between the Fear-Greed index and overall trader profitability.
- Why it matters: Measures how the strength of the sentiment–performance relationship changes over time, highlighting dynamic market conditions.
- Key insight: The correlation fluctuates — at times strongly positive (sentiment aligns with PnL) and at times near zero or negative, showing sentiment is not a constant predictor.



## 6. Volatility–Sentiment–PnL Interaction

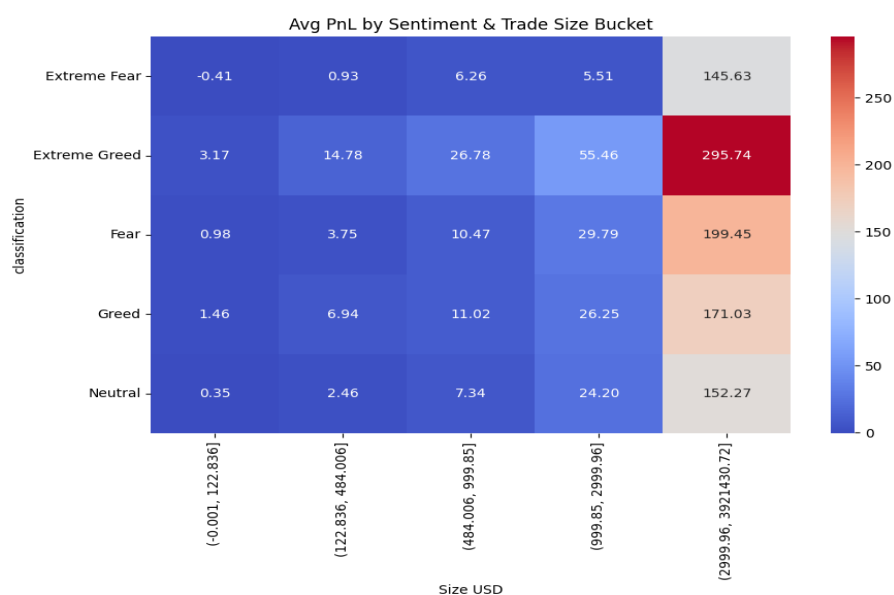
- Description: Created 3D plots mapping FG volatility, sentiment score, and average PnL.
- Why it matters: Uncovers combined effects of volatility and sentiment that are not visible in single-factor analysis.
- Key insight: High volatility with neutral sentiment often leads to the most unpredictable performance.

3D Interaction: Volatility, Sentiment, PnL



## 7. Avg PnL by Sentiment & Trade Size

- Description: Compares average capped Closed PnL across different trade size buckets, segmented by sentiment category.
- Why it matters: Shows whether larger or smaller trades yield better profitability in bullish vs bearish sentiment regimes.
- Key insight: Larger trades in Greed phases often produce higher average returns, while in Fear phases they may carry higher loss risk.



## **Conclusion :-**

Analysis of ~211k trades linked with Bitcoin market sentiment reveals that sentiment impacts trading performance, but effects vary with volatility, trade size, and trader style.

From the EDA, Greed phases generally show higher win rates and average PnL, while Fear can still produce selective high-return opportunities, especially during recoveries. Most trades cluster around small PnLs, and higher sentiment volatility drives larger swings in results.

Advanced methods show that Extreme Greed produces the biggest elite-trader wins, but Neutral and mild Fear phases sometimes offer better risk-adjusted returns. Large trades work best in Greed but are risky in Fear. Rolling correlations confirm that sentiment's predictive power changes over time, and sentiment flips often cause short-term drawdowns.

Key takeaway: A regime-aware strategy — adjusting position size, trade frequency, and timing to sentiment level and volatility — can improve both profitability and risk control.