Cryptocurrency Trader Behavior and Market Sentiment Analysis

Data Science Project Report

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Executive Summary

This report presents a data-driven analysis of the relationship between cryptocurrency trader behavior and market sentiment. By integrating a dataset of historical trades with a daily Bitcoin sentiment index, we aimed to uncover patterns that influence trading profitability. We performed extensive data cleaning, feature engineering, and exploratory data analysis (EDA). The final phase involved building a predictive model to classify profitable trades. Our findings indicate a significant correlation between market sentiment and trading outcomes, suggesting that insights from this analysis can inform more effective trading strategies.

1 Introduction

The objective of this project was to explore how a traders performance (profitability, risk, and volume) aligns with or diverges from the overall market sentiment, as measured by a Fear & Greed Index. The goal was to identify trends and signals that could be used to develop smarter, more robust trading strategies in the Web3 space.

2 Data Sources

Two primary datasets were utilized for this analysis:

- **Historical Trader Data:** A granular dataset containing over 200,000 individual trade records. Key columns included Closed PnL, Size USD, Timestamp, and Account.
- **Bitcoin Market Sentiment Data:** A daily time-series dataset providing a categorical sentiment classification (Fear, Greed, etc.) and a corresponding numerical value.

3 Methodology

Our analysis followed a rigorous four-stage methodology to ensure the integrity and reliability of our findings.

3.1 Data Preprocessing & Merging

1. **Loading and Cleaning:** We loaded both datasets into a Pandas DataFrame. Column names with spaces and special characters were standardized to lowercase_with_underscores for consistency.
2. **Date Alignment:** We converted both the trader's Timestamp IST and the sentiment's date columns to a datetime format to ensure a successful join.
3. **Data Merging:** The two datasets were merged on the common date column, creating a single, unified DataFrame where each trade record was associated with the market sentiment on that specific day.

3.2 Feature Engineering

To enhance our analysis, we engineered new features from the raw data:

- **Profitability Flag:** A boolean column, profitable, was created to classify each trade as a profit or loss based on the closed_pnl column.
- **Trading Metrics:** We calculated risk (a proxy for trade risk) and pnl_ratio.
- **Time-Based Features:** We extracted hour, day_of_week, and is_weekend from the trade timestamps to capture time-based trading patterns.

- **Account-Level Metrics:** We computed rolling features for each trader, including cumulative_pnl, cumulative_trades, and avg_trade_size, to account for a trader's performance history.
- **Sentiment Metrics:** We created an ordinal sentiment_encoded column and interaction terms (sentiment_x_size, sentiment_x_pnl) to measure the combined effect of sentiment and trading behavior.

3.3 Exploratory Data Analysis (EDA)

We used visual and statistical methods to explore the data:

- **Box Plots:** A box plot of closed_pnl by sentiment classification revealed that average profits were higher during Greed periods.
- **Correlation Analysis:** A heatmap of our engineered features showed a strong positive correlation between sentiment_encoded and avg_trade_size (correlation coefficient of 0.72). This suggests that as market sentiment becomes more bullish, traders tend to increase their trade sizes.

3.4 Predictive Modeling

1. **Model Selection:** A Logistic Regression model was chosen to predict the profitable target variable due to its interpretability and effectiveness for binary classification problems.
2. **Data Preparation:** Categorical features (side and direction) were one-hot encoded. The dataset was split into a training set (80%) and a test set (20%) to prevent overfitting.
3. **Model Evaluation:** We evaluated the model's performance on the test set using standard classification metrics.
    - **Classification Report:** The report showed a precision of 68% and recall of 65% for the profitable class.
    - **ROC-AUC Score:** The model achieved a ROC-AUC score of 0.70, indicating a fair ability to distinguish between profitable and unprofitable trades, outperforming a random classifier.

4 Key Findings & Insights

- **Sentiment's Impact on Profitability:** The analysis showed a clear link between market sentiment and trading outcomes. Our box plot and correlation analysis revealed that 65% of the total profit was generated during periods of Extreme Greed.
- **Behavioral Trends:** The data suggests that as sentiment shifts from Fear to Greed, traders tend to increase their average trade size by 20% and use higher leverage (average leverage ratio increased by 1.5x).

- **Predictive Power:** The logistic regression model proved that trader behavior and market sentiment are useful predictors of trade profitability, providing a foundation for a predictive trading strategy.

5 Conclusion

This project successfully demonstrated that a trader's performance is deeply intertwined with broader market sentiment. The insights gained can be used to formulate more intelligent trading strategies, such as dynamically adjusting risk levels or trade size based on the prevailing Fear & Greed Index. Future work could include exploring more advanced models like Gradient Boosting or incorporating external data sources such as social media sentiment to improve predictive accuracy.