Trader Performance and Market Sentiment Analysis

1. Objective

This project aims to analyze the relationship between trader performance and market sentiment using two primary datasets: the Bitcoin Market Sentiment Dataset (Fear-Greed Index) and Historical Trader Data from Hyperliquid. The objective was to merge these datasets, explore how market emotions such as 'Fear' and 'Greed' impact trading behavior, and identify patterns that can inform smarter trading strategies.

2. Dataset Overview

The analysis was conducted using two datasets:

1. Bitcoin Market Sentiment Dataset – Contains Date, Value, and Classification (Fear/Greed categories).

2. Historical Trader Data – Includes trade-level details such as Timestamp, Coin, Side, Execution Price, Size, Start Position, Fee, Closed PnL, and Direction.

3. Data Merging Process

Both datasets were merged on a common 'date' column after converting timestamps to date-only formats. The merged dataset provided a unified view of market sentiment and trader performance on the same day.

4. Predictive Modeling

The initial phase involved training a RandomForestClassifier to predict trading behavior ('Direction') based on both trader and sentiment features. The model achieved an accuracy of 99.2% on the test split.

5. Expected Profit and Loss (PnL) Analysis

A custom function was designed to compute Expected PnL using the formula: ((Closed PnL - Fee) / Start Position) * Value. This function was compared with a machine learning regression model (RandomForestRegressor) trained to predict Expected PnL.

Key observation: The mathematical function closely matched actual PnL values for sampled trades and outperformed the ML model on several samples. The regression model showed poor R^2 (negative) and high MAE in this run, suggesting mismatch or data quality / feature issues for modeling PnL directly.

6. SHAP Explainability

SHAP (SHapley Additive exPlanations) was applied to interpret the RandomForest regression model. Results indicated that 'Size USD', 'hour', and 'month' were among the most influential variables driving Expected PnL, while sentiment indicators such as 'Fear' and 'Greed' typically had secondary effects.

7. Influential Coins on Expected PnL

SHAP feature importance analysis revealed the top coins with the highest impact on Expected PnL. This identifies which assets contribute most significantly to profitability under varying market sentiments.

8. Trader Behavior Clustering

Using KMeans clustering on features such as Value, Fee, Closed PnL, Start Position, and Expected PnL, four trader categories were identified:

• High PnL, Low Fees (Efficient Traders)

• Low Sentiment & Low Profit (Fearful Traders)

• High Volume, Moderate Profit (Aggressive Traders)

• Neutral Sentiment, Erratic Profit

Cluster centroids reveal behavioral differences and allow tailoring risk/position sizing rules to each group.

9. Risk Analysis

Risk analysis was added to quantify downside exposure and cluster-level risk characteristics. Key risk metrics computed during analysis included:
• Mean and median Expected PnL per cluster
• Standard deviation of PnL (volatility)
• Percentage of negative trades per cluster (downside frequency)
• Identification of outliers and singleton clusters with extreme PnL values
• Recommended Value-at-Risk (VaR) and stress-testing procedures

Observed cluster-level statistics (from this run):

• Cluster 0 — Mean Expected PnL ≈ 59.61, % negative trades ≈ 44.32 (count: 2085)

• Cluster 1 — Mean Expected PnL ≈ 53.06, % negative trades ≈ 48.37 (count: 2913)

• Cluster 2 — Mean Expected PnL extremely large (1.35e+08), count: 1 – likely an outlier / data error

• Cluster 3 — Mean Expected PnL ≈ 15,200, count: 1 – singleton with extreme value

Interpretation & actions:
- Clusters 0 and 1 capture the bulk of trades with similar mean returns but near ~45–48% negative rate, indicating substantial downside frequency. - Clusters 2 and 3 are singletons/outliers; investigate trade-level data for these rows (extreme leverage, incorrect Start Position, or data entry errors). - Compute VaR (e.g., 95% historical VaR) per cluster to quantify worst-case losses and implement position-sizing rules accordingly.

10. Dynamic Personality Analysis (LSTM Autoencoder)

A deep learning model (LSTM Autoencoder) was built to analyze temporal patterns in trader behavior. The network encoded 20-day sequences of features into a 16-dimensional latent representation, which was then clustered using KMeans. The results identified evolving market behavior regimes and transitions over time.

11. Final Insights

• Traders tend to perform better during periods of high market greed (75–94 range of the Fear-Greed Index).
• RandomForest classification performed well for predicting trade direction (99.2% accuracy) in this run.
• The function-based Expected PnL aligned closely with actual outcomes and outperformed the ML regression model on sampled tests.
• Market conditions such as time (hour/month) and trade size have stronger predictive power than sentiment alone.
• Risk metrics show substantial downside frequency (~44–48% negative trades) in the main clusters — emphasizes need for risk controls.

12. Model Performance Summary

RandomForestClassifier Accuracy: 99.2%
RandomForestRegressor R^2 Score: -1296.04 (indicating model wasn't a good fit for PnL prediction in this run)
Mean Absolute Error (Regression): 12061.89
Function-based Expected PnL (example): 0.0167 (aligned with actual)

13. Conclusion & Next Steps

The analysis successfully demonstrates relationships between trader-level features and market sentiment, and highlights the importance of explicit risk analysis. Next steps include: outlier remediation, cluster-specific VaR-driven position sizing, adding more robust features (rolling volatility, drawdown metrics), and validating models per sentiment regime.