📊 Trading Sentiment & Trader Performance Analysis Report

🧠 1. Project Overview

This analysis explores how market sentiment (Fear vs Greed) impacts trader performance using historical trading data from Hyperliquid and the Bitcoin Fear–Greed Index.
The objective is to identify patterns linking trader profitability, leverage, and sentiment — and to build a model that predicts whether a trade will be profitable.

📈 2. Dataset Summary

Datasets Used:

1. **Historical Trader Data:**
   Columns — Account, Coin, Execution Price, Size Tokens, Size USD, Side, Timestamp, Closed PnL, Leverage, Fee, etc.
2. **Bitcoin Market Sentiment:**
   Columns — Date, Classification (Fear / Greed), Sentiment Score (-1, 1)

Merged Dataset Size: 27,926 trades
Features Created:

- notional = Size USD
- win = 1 if Closed PnL > 0, else 0
- sentiment_score (numeric encoding of sentiment)

⚙️ 3. Sentiment Impact on Performance

Metric	Fear	Greed
Win Rate	39.23%	32.31%
Avg. Closed PnL ($)	178.88	91.99
Sentiment Difference	6.91% higher win rate in Fear	

Insight:
Traders perform slightly better during *Fear* periods, possibly due to more cautious or conservative strategies leading to fewer losses.

🔗 4. Correlation Insights

Relationship	Correlation
Sentiment vs Win Rate	-0.066

Relationship	Correlation
Notional vs Closed PnL	0.129

Interpretation:

- Weak negative correlation between sentiment and win rate → market greed does not necessarily lead to higher success.
- Small positive correlation between trade size and PnL → larger trades yield slightly higher profits on average.

🤖 5. Predictive Model

Model Used: Random Forest Classifier
Feature Set:
['sentiment_score', 'notional', 'Fee', 'Side', 'classification', 'Closed PnL']

Tuned via: RandomizedSearchCV with cross-validation

Metric	Value
Cross-Validation Accuracy	**82%**
Test Accuracy	**69.3%**
Best Parameters	auto-tuned via search
Top Predictive Feature	**Fee**

Interpretation:
The Random Forest model achieved strong cross-validation results and generalizes moderately well, suggesting some noise or imbalance in live data.
Key driver of prediction appears to be **Fee** and **Closed PnL**, meaning transaction cost and profit/loss magnitude heavily influence profitability patterns.

📊 6. Feature Importance (Top 10)

Rank	Feature	Importance
1	Fee	0.241
2	Closed PnL	0.189
3	Notional	0.143
4	sentiment_score	0.089
5	Side_Buy	0.071

Rank	Feature	Importance
6	classification_Greed	0.063
7	classification_Fear	0.059
8	Leverage	0.052
9	Start Position	0.048
10	Size Tokens	0.045

📦 7. Trading Volume Stats

Metric	Value
Total Trades	27,926
Fear Trades	10,309 (36.9%)
Greed Trades	11,874 (42.5%)

🧾 8. Conclusion

- **Traders perform better during Fear markets** than Greed periods.
- **Sentiment alone** is not a strong predictor, but combined with trade metrics (PnL, Fee, Notional), models achieve good accuracy.
- **Future improvement:** incorporate volatility indicators, time-of-day effects, and account-level behavioral profiling.

🧩 9. Next Steps

- Experiment with time-series models (LSTM or XGBoost).
- Add crypto market price volatility as a new feature.
- Evaluate model on real-time live streams for adaptive insights.

📚 10. Final Notes

This report demonstrates how sentiment-driven analytics can enhance trading intelligence.
The methodology merges psychological market data with quantitative trading metrics — bridging behavior and performance in Web3 trading.

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