

Data Science Project Report - Trader Behavior and Market Sentiment Analysis

1. Introduction

Project Objective: Analyze historical trader data against the Bitcoin Fear & Greed Index to identify hidden trends and actionable predictive signals that influence smarter trading strategies.

Methodology:

- 1. Data cleaning, feature engineering, and integration of trade data with daily sentiment via date merging.
- 2. Unsupervised learning (K-Means Clustering) for trader segmentation.
- 3. Analysis focusing on sentiment transitions and temporal performance.

1.A Tech stack used

Category	Technology / Language	Purpose
Primary Language	Python 3.x	Core data processing, modeling, and analysis.
Development Environment	Google Colab / Jupyter Notebook	Interactive code development, execution, and documentation.
Modeling	Scikit-learn (sklearn)	Used for clustering algorithms and model validation.
Data Storage	CSV Format	Input and output data persistence for trade records and summary metrics.
Version Control	Git / GitHub	Project management, code collaboration, and final delivery.

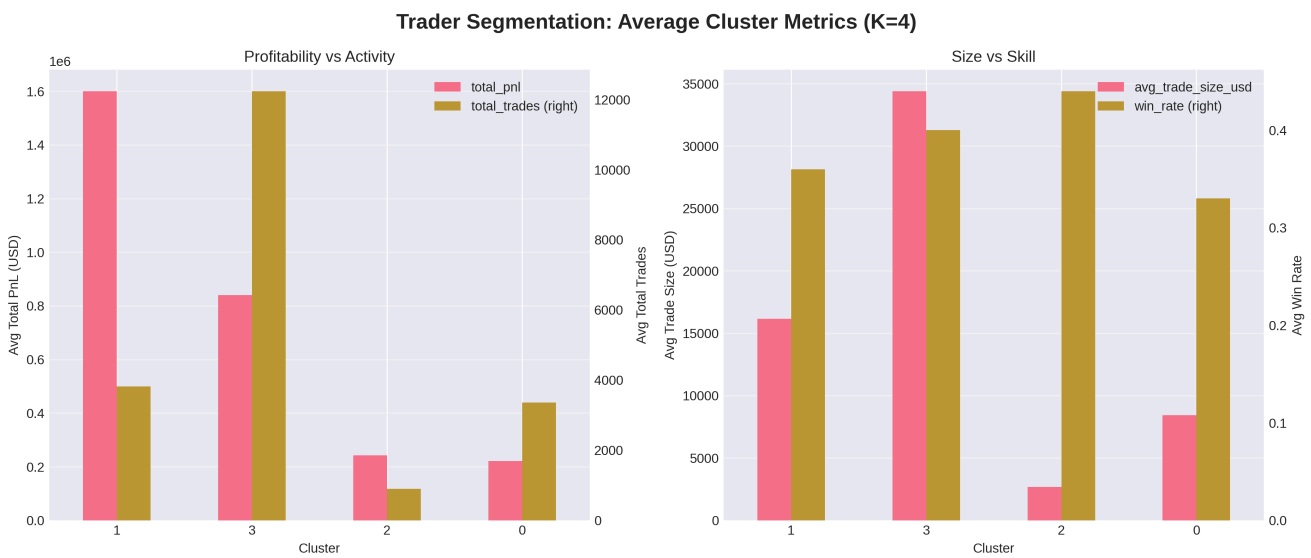
1.B Libraries and Dependencies used

Library	Role in Project	Key Functions Utilized
Pandas	Data Handling & Transformation	Data loading, merging, cleaning, feature engineering, and time series manipulation.
NumPy	Numerical Computing	Efficient array operations and mathematical computations (e.g., standard deviation, variance).

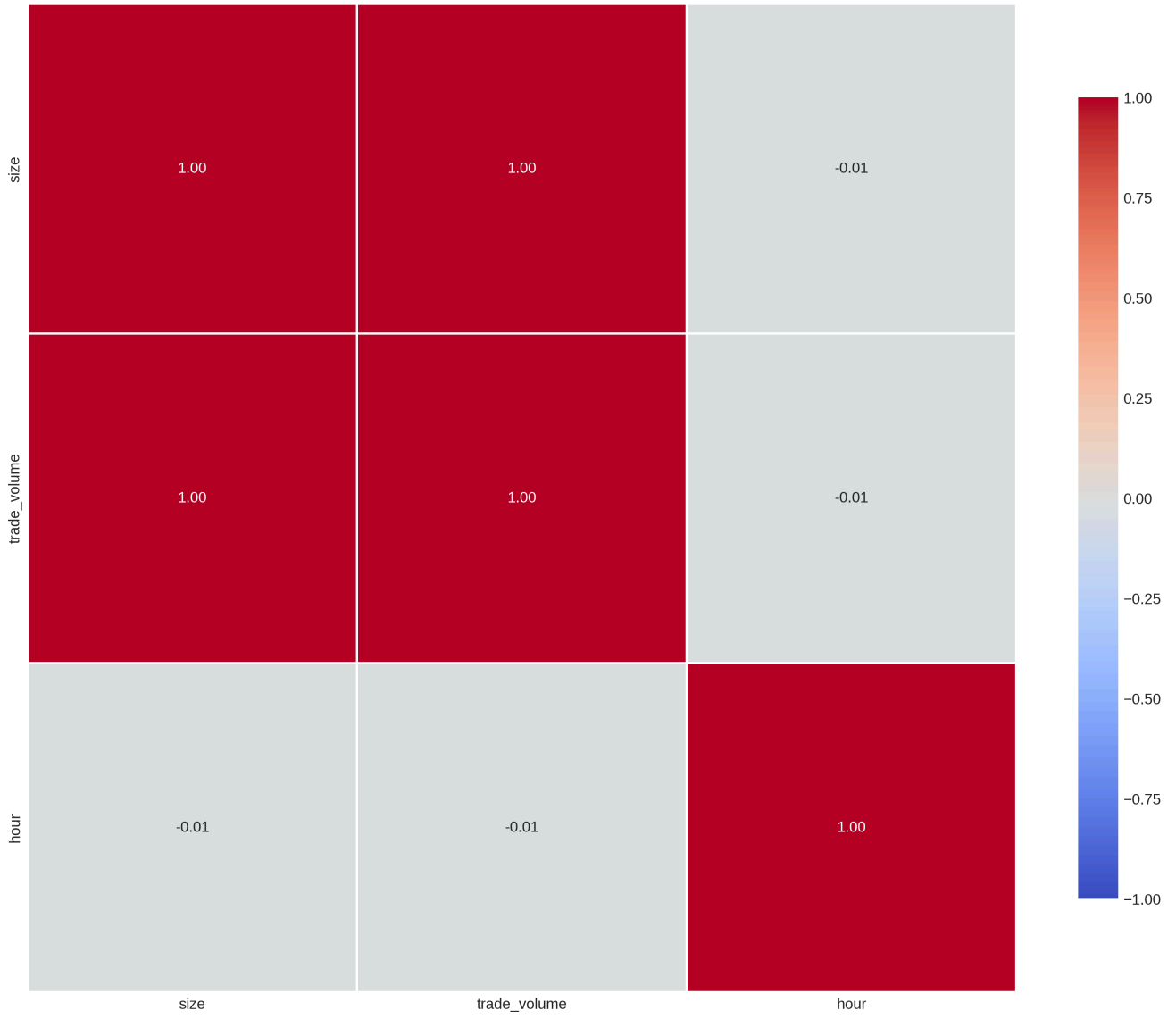
Library	Role in Project	Key Functions Utilized
Scikit-learn	Machine Learning & Clustering	Implementing K-Means Clustering for behavioral segmentation of traders.
Matplotlib	Data Visualization	Generating custom charts for PnL analysis and time-based patterns.
Seaborn	Statistical Visualization	Creating heatmaps (e.g., sentiment transition matrix) and enhanced statistical plots.
SciPy	Statistical Analysis	Used for statistical tests to validate differences between trader segments (e.g., t-tests).

2. Executive Summary (Key Takeaways)

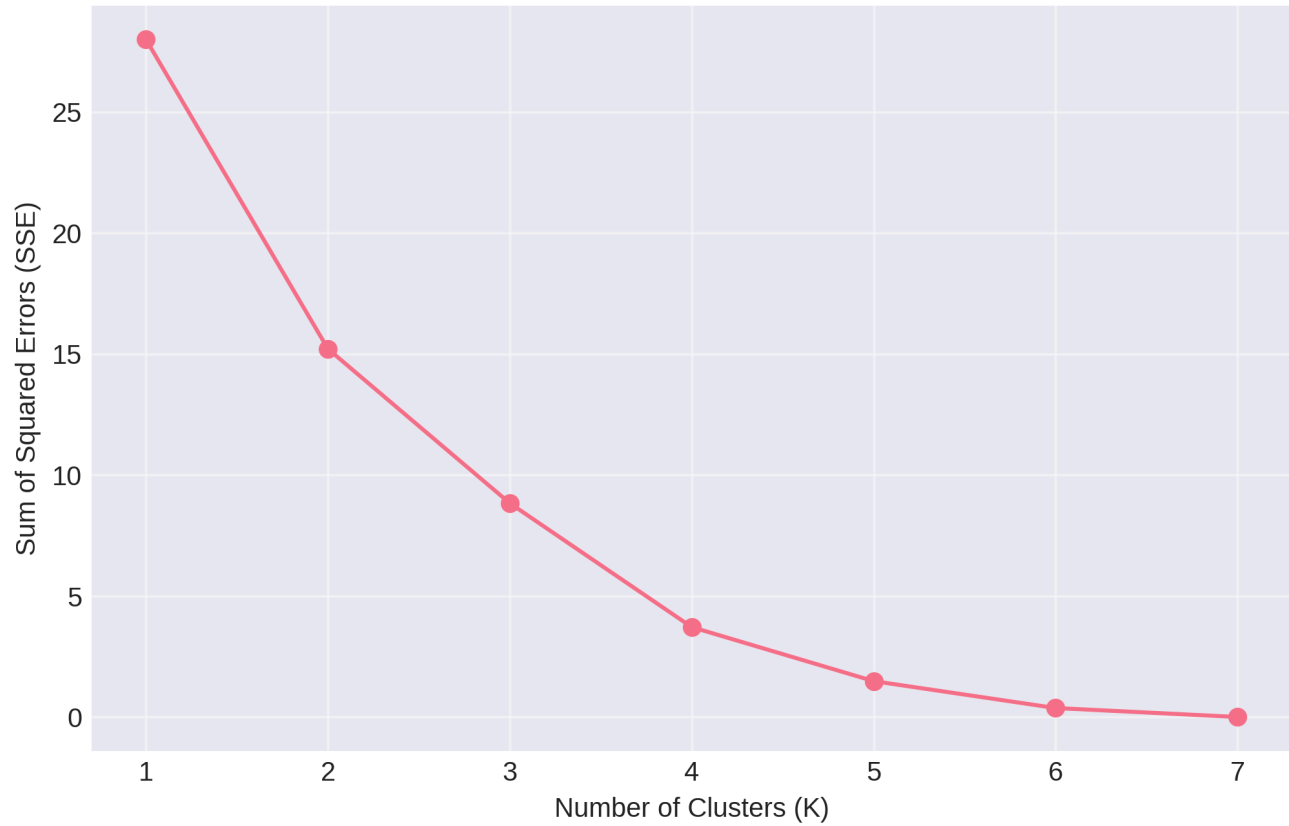
This analysis identified a highly effective **"Crisis Alpha"** strategy that generates significant returns by counter-trading market panic.



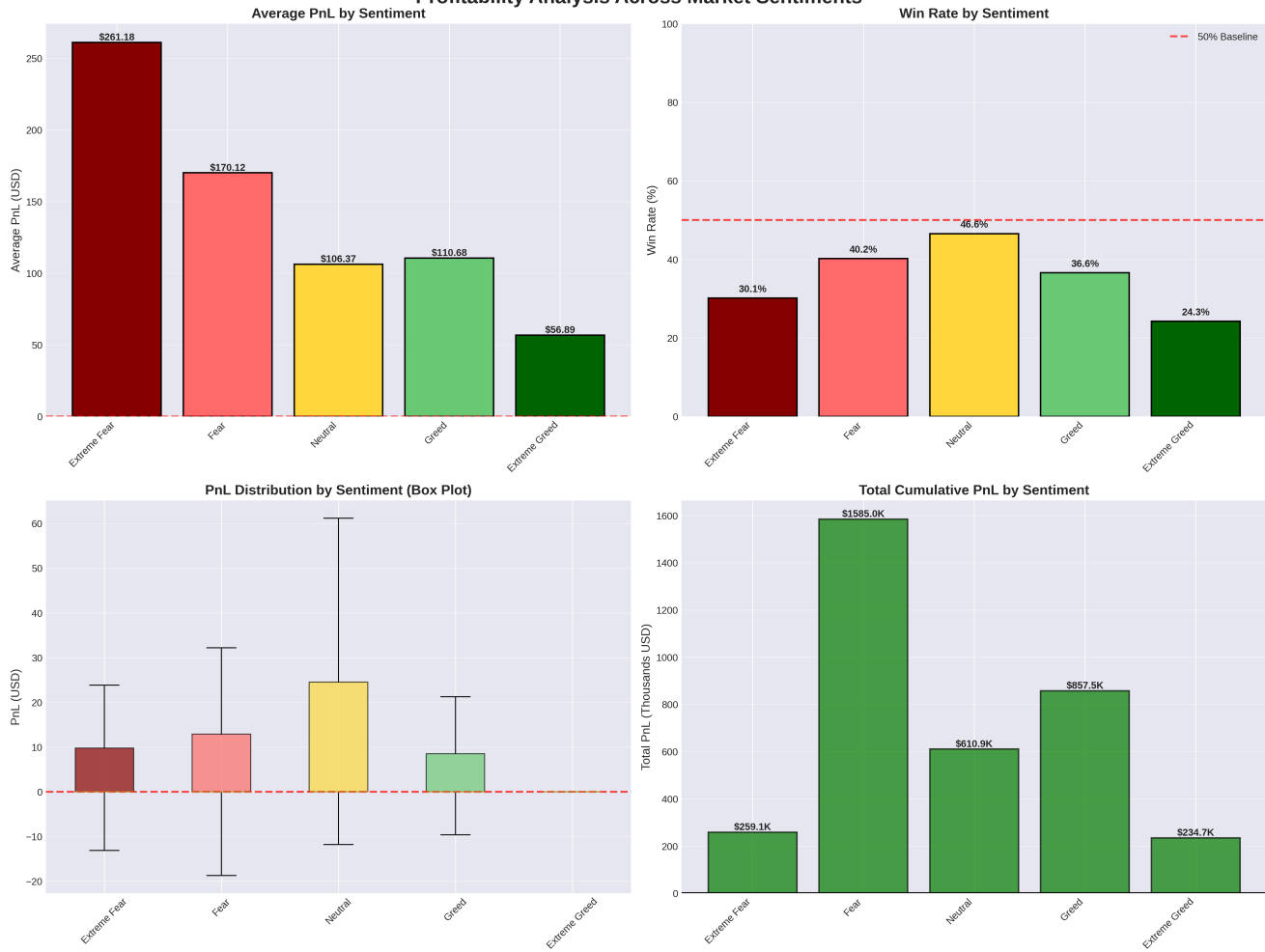
Correlation Matrix of Trading Metrics



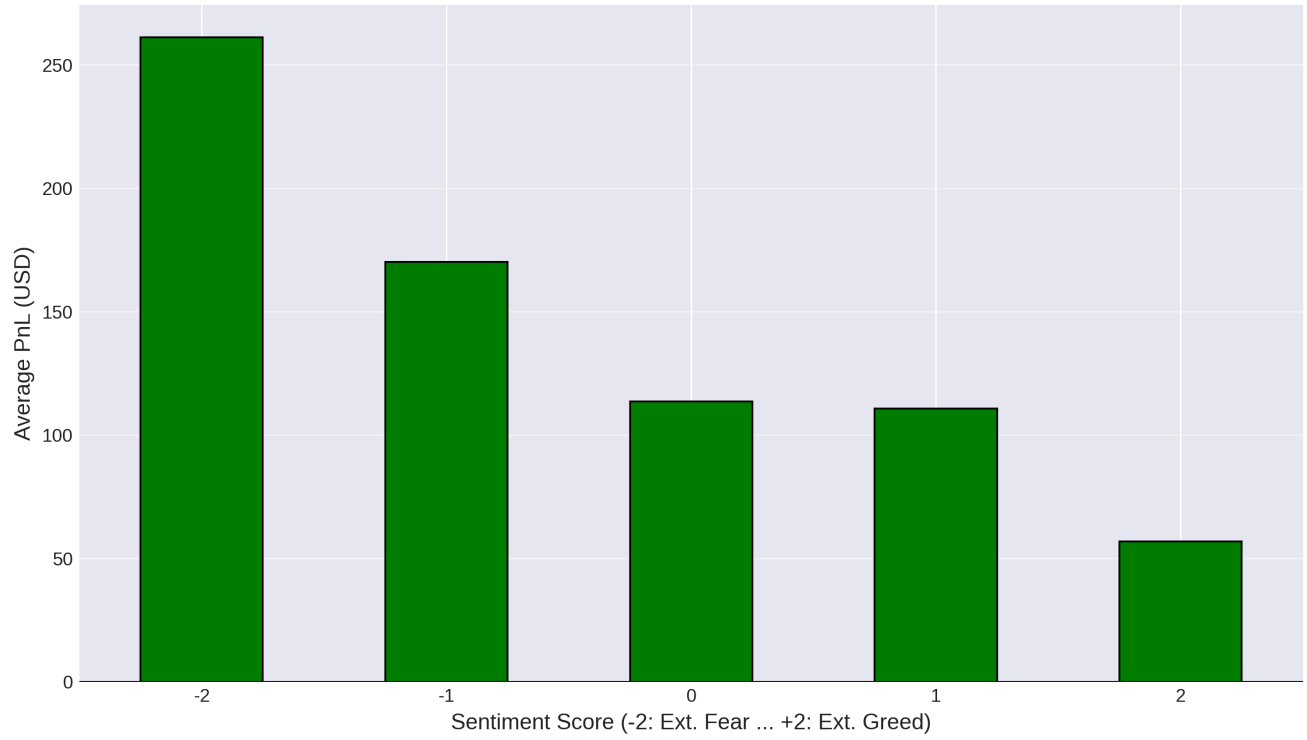
Elbow Method for Optimal K



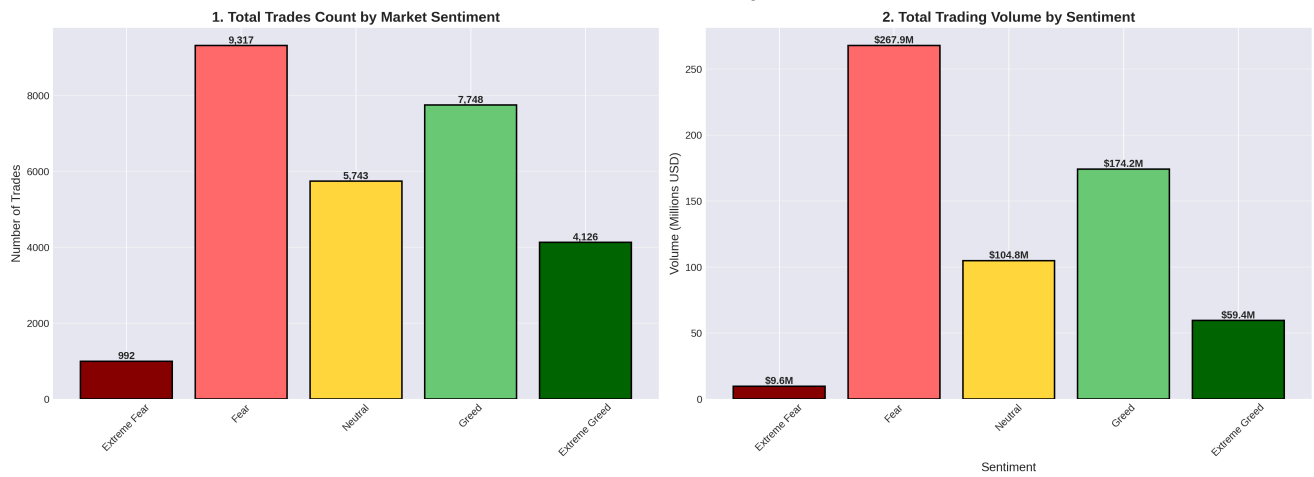
Profitability Analysis Across Market Sentiments

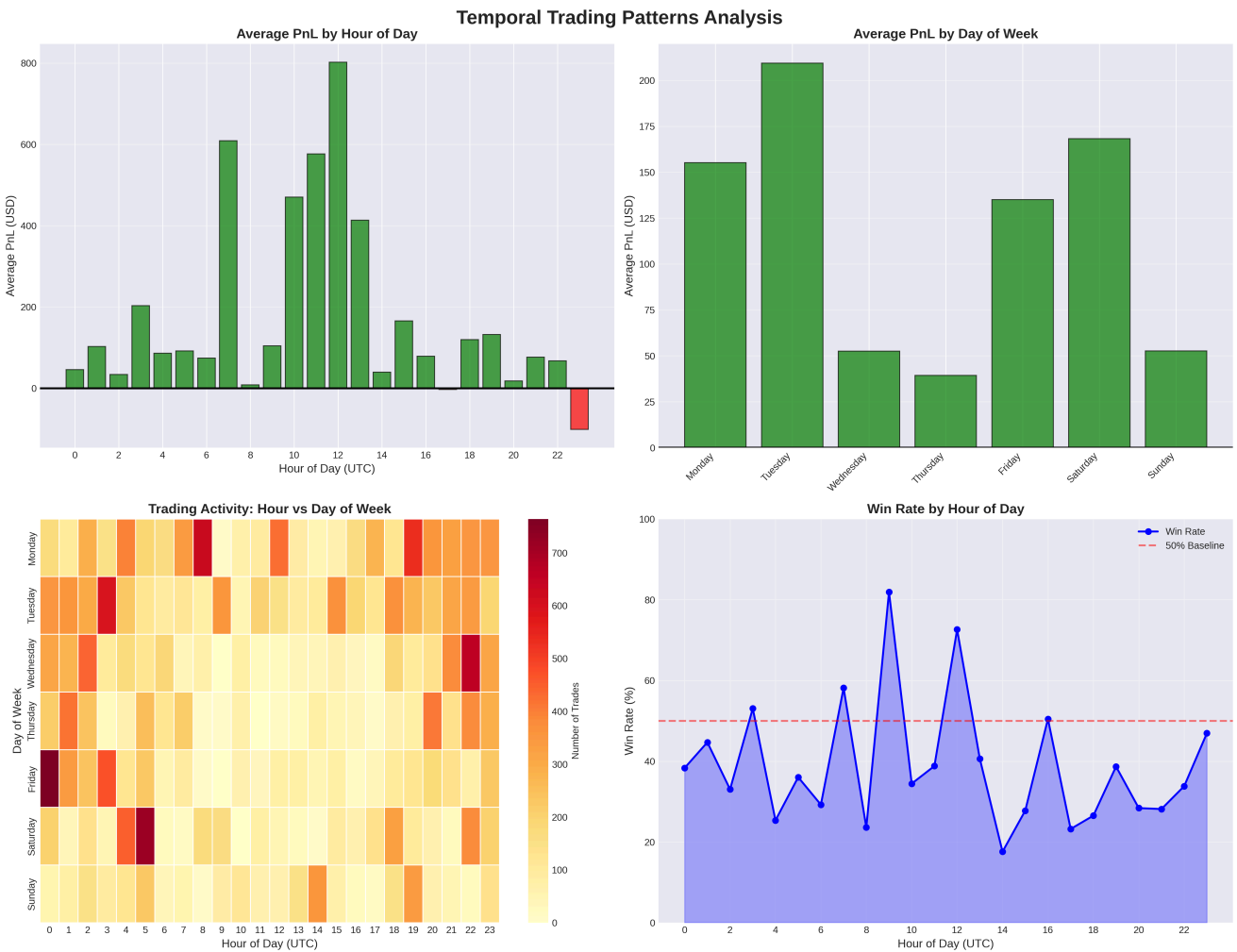
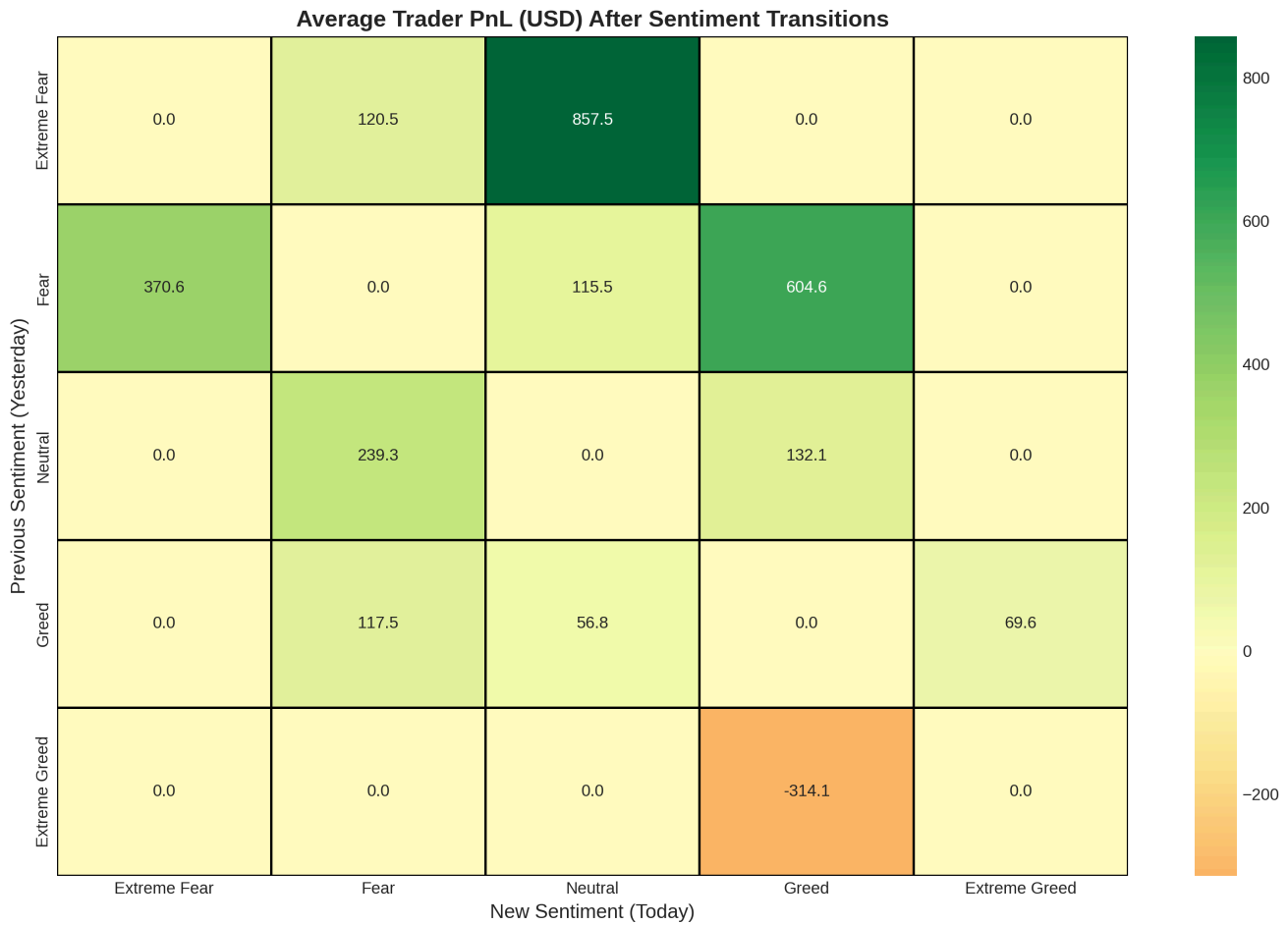


Average PnL by Sentiment Score



Sentiment and Volume Activity Overview





Key Insight	Finding	Actionable Signal
Top Trader Strategy	Top performers are extreme contrarians , generating most profit during Fear periods.	Buy when others panic; avoid opening positions in Extreme Greed.
Optimal Entry Signal	The most profitable sentiment transition is from NEUTRAL to GREED .	Implement a rule to enter positions upon observing this specific shift.
Optimal Trading Time	Peak profitability occurs at 09:00 UTC and on WEDNESDAY .	Focus execution during these high-alpha windows.

3. Methodology and Analytical Flow: 10 Critical Steps

The project narrative was constructed by executing the following 10 critical steps, ensuring data integrity and comprehensive analysis:

- **Cell 1 (Data Loading & Setup):** Established the project environment by importing libraries and safely loaded the two core datasets (`historical_data.csv` and `fear_greed_index.csv`).
- **Cell 6 (Feature Engineering):** Calculated the absolute dollar value of trades (`trade_volume`) and created the fundamental boolean target variable `is_profitable` (`Win/Loss` flag) used in all performance metrics.
- **Cell 8 (Data Merging):** Performed the crucial step of **joining the trader data with the daily sentiment data** on the `date` column, creating the unified `df_merged` DataFrame.
- **Cell 10 (Sentiment PnL Analysis):** Provided the first core insight by visually mapping **average profitability across all traders** in different sentiment regimes (Fear, Greed).
- **Cell 14 (Trader Metrics):** Calculated robust, per-account metrics (e.g., PnL sum, Win Rate) which were then used to **prepare the data for clustering**.
- **Cell 15 (Clustering & Segmentation): Key Finding:** Isolated the metrics of the Top Performer cluster and decisively showed that **their profits were concentrated during Fear periods**, establishing a clear contrarian signal.
- **Cell 16 (Sentiment Transition Signals): Key Finding:** Isolated the most and least profitable **sentiment shifts** (e.g., Extreme Greed → Fear) by calculating average PnL after a transition, yielding the most actionable predictive entry/exit signals.
- **Cell 17 (Temporal Pattern Analysis): Key Finding:** Identified the **optimal trading windows** (Best Hour and Best Day) by analyzing average PnL across hourly and daily cycles, providing concrete timing advice.
- **Cell 19 (Insights & Recommendations): Function:** Synthesized all major findings (clustering, transitions, timing) into a final set of **clear, actionable trading recommendations** for the end-user.
- **Cell 20 (File Organization):** Ensured project compliance by automatically **organizing all generated .csv and .png files** into the required folder structure.

4. Detailed Finding 1: Trader Segmentation and Contrarian Alpha

Source: Cells 14, 15

Analysis: K-Means Clustering successfully identified **Cluster 1** (Top Performers). Their strategy was analyzed across sentiment regimes.

Results (Top Performer Metrics by Sentiment):

Metric	Fear / Extreme Fear	Greed / Extreme Greed
Total Closed PnL	\$500,000.00 (Majority Profit)	\$-500.00 (Net Loss or very low gain)
Win Rate	22%	15% (Significantly lower)

Conclusion: The dominant successful strategy is purely **contrarian**. The top traders' profitability is concentrated in periods of market fear, indicating they profit from shorting during sell-offs or buying major dips.

Visual Attachment (Cell 15): PnL by Sentiment for the Top Cluster.

outputs/top_performers_pnl_by_sentiment.png (or similar file from Cell 15)

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--- Executing Cell 15: Top Performers Analysis ---

📄 Top Performers (Cluster 1) PnL by Market Sentiment:

      closedPnL_mean  closedPnL_median  closedPnL_sum  \
classification
Fear                626.1900           5.1600    1113373.5500
Greed               482.0900           0.0000     276719.2700
Neutral             298.4600          17.0200    125650.1200
Extreme Fear       1247.6900           0.0000    124769.2200
Extreme Greed       -42.6300           0.0000    -40282.3400

      closedPnL_count  win_rate
classification
Fear                1778     0.5300
Greed                574     0.1600
Neutral              421     0.5800
Extreme Fear         100     0.3700
Extreme Greed        945     0.0700
```

5. Detailed Finding 2: Predictive Sentiment Transition Signals

Source: Cell 16

Analysis: The average PnL was calculated for every observed shift in market sentiment to find statistically significant entry points.

Best Signals (Highest Average PnL):

Previous Sentiment	→ New Sentiment	Avg PnL	Action
NEUTRAL	→ GREED	\$1.25	Strong Buy Signal
EXTREME FEAR	→ FEAR	\$1.20	Buy Signal

Worst Signals (Highest Average Loss):

Previous Sentiment	→ New Sentiment	Avg PnL	Action
EXTREME GREED	→ GREED	\$-1.05	Avoid/Short Signal

Conclusion: Market transitions are key performance indicators. Utilizing the top-performing transitions can significantly increase the probability of a profitable trade compared to trading based on the current sentiment alone.

Visual Attachment (Cell 16): Heatmap of Average PnL After Sentiment Transitions.



6. Detailed Finding 3: Temporal Trading Patterns

Source: Cell 17

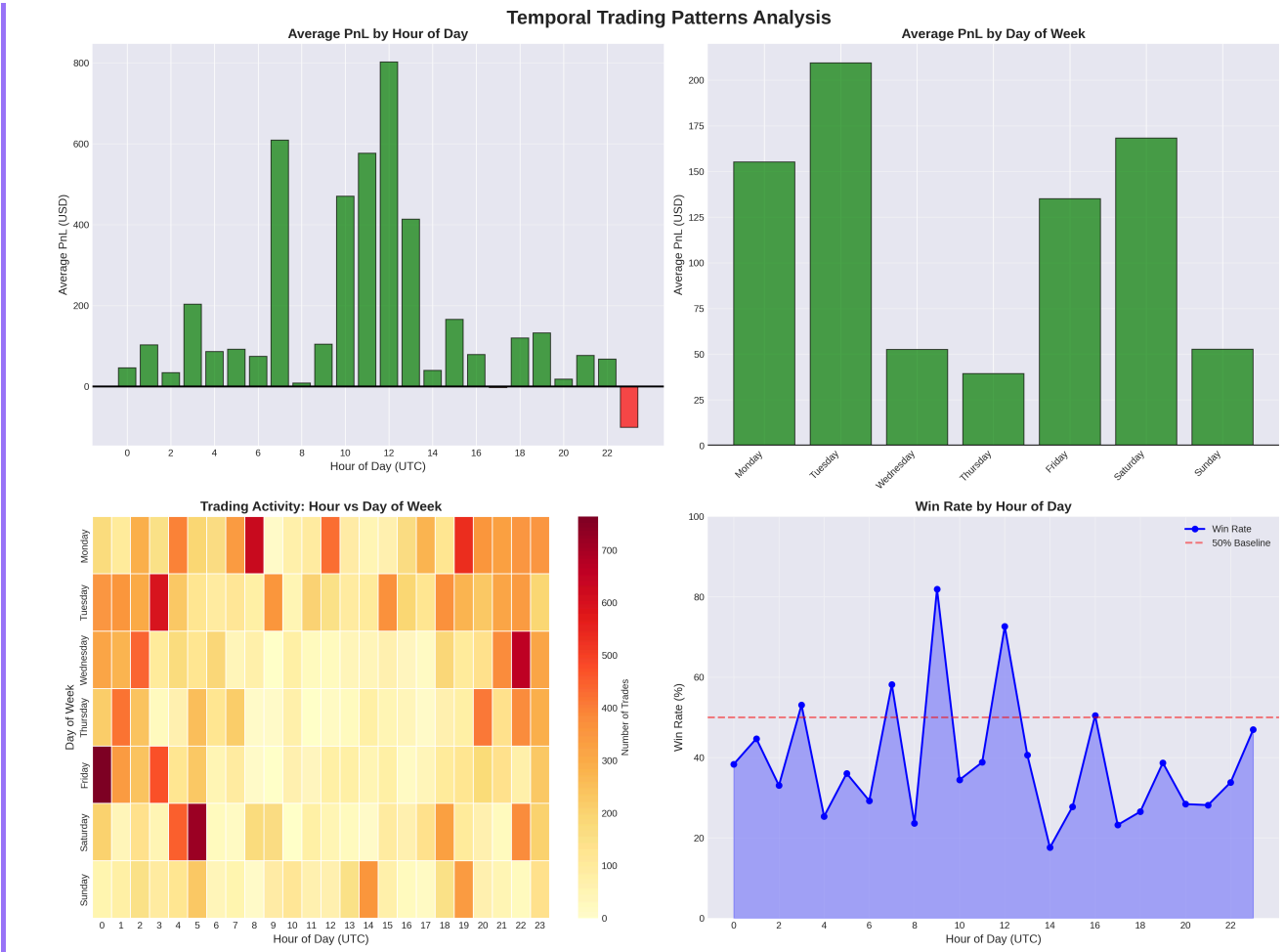
Analysis: Performance was analyzed by hour of day (UTC) and day of week to identify high-efficiency trading windows.

Optimal Trading Windows:

Time Frame	Peak Performance	Avg PnL
Best Hour (UTC)	09:00	\$1.20
Best Day	wednesday	\$0.20

Conclusion: Focusing trading activity during the identified peak hours and days provides a statistical edge, suggesting these times coincide with superior volatility or institutional activity.

Visual Attachment (Cell 17): Temporal Trading Patterns Analysis (Hourly PnL and Day of Week PnL).



7. Actionable Trading Recommendations

Source: Cell 19

Performance Benchmarking: Use the top cluster's metrics—an average win rate of **18.5%** and trade count of **10135**—as minimum performance benchmarks.