Acknowledgement

I express my sincere gratitude to **Primetrade.ai** for offering me this valuable internship opportunity in the field of **Data Science** through **Internshala**. The assignment provided was insightful and gave me practical exposure to real-world data analysis and predictive modeling using machine learning.
I am thankful to the **Primetrade.ai team** for curating such a well-structured and challenging task, which allowed me to enhance my technical skills and deepen my understanding of data science concepts.
Lastly, I extend my appreciation to everyone who supported me, directly or indirectly, throughout this learning journey.

Thilak

Title of the Project: Analyzing Trader Behavior Under Market Sentiment Dynamics

Aim: To analyze the relationship between market sentiment (Fear & Greed Index) and trading behavic using real trader data, identifying how sentiment affects trade size, profitability, and decision-making**.**

Name of the tool used: Google Colab (Python, Pandas, Seaborn, Plotly)

Objectives:

1. To merge and preprocess different financial datasets — for example, past trade history and the Fear & Greed Index — to permit comparative analysis. It involves cleaning data, formatting, timestamp synchronizing, and joining on shared temporal key.
2. To investigate the impact of prevailing sentiment on trade behavior with the aim to understand if "Fear" or "Greed" time frames are related to trade volume fluctuations, price of execution, position side, and subsequent profit or loss (PnL).
3. To demonstrate trade profitibility and risk-taking behavior within sentiment categorizations, utilizing modern data visualization libraries like Seaborn and Plotly to present trends, outliers, and distributions on key variables such as Closed PnL and Trade Size.

Full Python Code with Steps & Explanations:

Step 1: Import Required Libraries:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import warnings
warnings.filterwarnings('ignore')
```

Step 2: Load the CSV Files:

```
trader_data = pd.read_csv('historical_data.csv')
sentiment_data = pd.read_csv('fear_greed_index.csv')
```

Step 3: Parse Dates Properly:

```
trader_data['Timestamp'] = pd.to_datetime(trader_data['Timestamp IST'], errors='coerce')
trader_data['date'] = trader_data['Timestamp'].dt.date
sentiment_data['date'] = pd.to_datetime(sentiment_data['date'], errors='coerce').dt.date
sentiment_data['classification'] = sentiment_data['classification'].str.strip().str.title()
```

Step 4: Filter Trader Data by Valid Sentiment Dates:

```
valid_dates = sentiment_data['date'].unique()
trader_data = trader_data[trader_data['date'].isin(valid_dates)]
```

Step 5: Step 5: Merge Datasets:

```
df = pd.merge(trader_data, sentiment_data[['date', 'classification']], on='date', how='left')
print("✅ Sentiment distribution:")
print(df['classification'].value_counts(dropna=False))
```

Step 6: Preview and Validate Merged Data:

```
df[['Account', 'Execution Price', 'Size USD', 'Side', 'Closed PnL', 'classification']].head()
```

Step 7: Visual Analysis (EDA):

7.1 – Market Sentiment Distribution

```
sns.countplot(data=df, x='classification', palette='Set2')
plt.title('🧠 Market Sentiment Distribution')
plt.xlabel('Sentiment')
plt.ylabel('Number of Records')
plt.show()
```

7.2 – Profitability vs Sentiment

```
plt.figure(figsize=(10, 5))
sns.stripplot(data=df, x='classification', y='Closed PnL', palette='Set1', jitter=True)
plt.title('💰 Profitability vs Market Sentiment (Strip Plot)')
plt.xlabel('Sentiment')
plt.ylabel('Closed PnL')
plt.grid(True)
plt.tight_layout()
plt.show()
```

7.3 – Trade Size vs Sentiment

```
plt.figure(figsize=(10, 5))
sns.boxplot(data=df, x='classification', y='Size USD', palette='Blues')
plt.title('📈 Trade Size vs Market Sentiment')
plt.xlabel('Sentiment')
plt.ylabel('Trade Size (USD)')
plt.show()
```

7.4 – Interactive PnL vs Size

```
fig = px.scatter(
  df,
  x='Size USD',
  y='Closed PnL',
  color='classification',
  title='🌀 PnL vs Trade Size (by Sentiment)',
  hover_data=['Account', 'Side', 'Execution Price']
)
fig.show()
```

Step 8: Summary Stats by Sentiment:

```
df.groupby('classification')[['Closed PnL', 'Size USD']].agg(['mean', 'median', 'std']).round(2)
```

Outcome of the work:
Input and output:

1. Historical Trader Data (historical_data.csv)

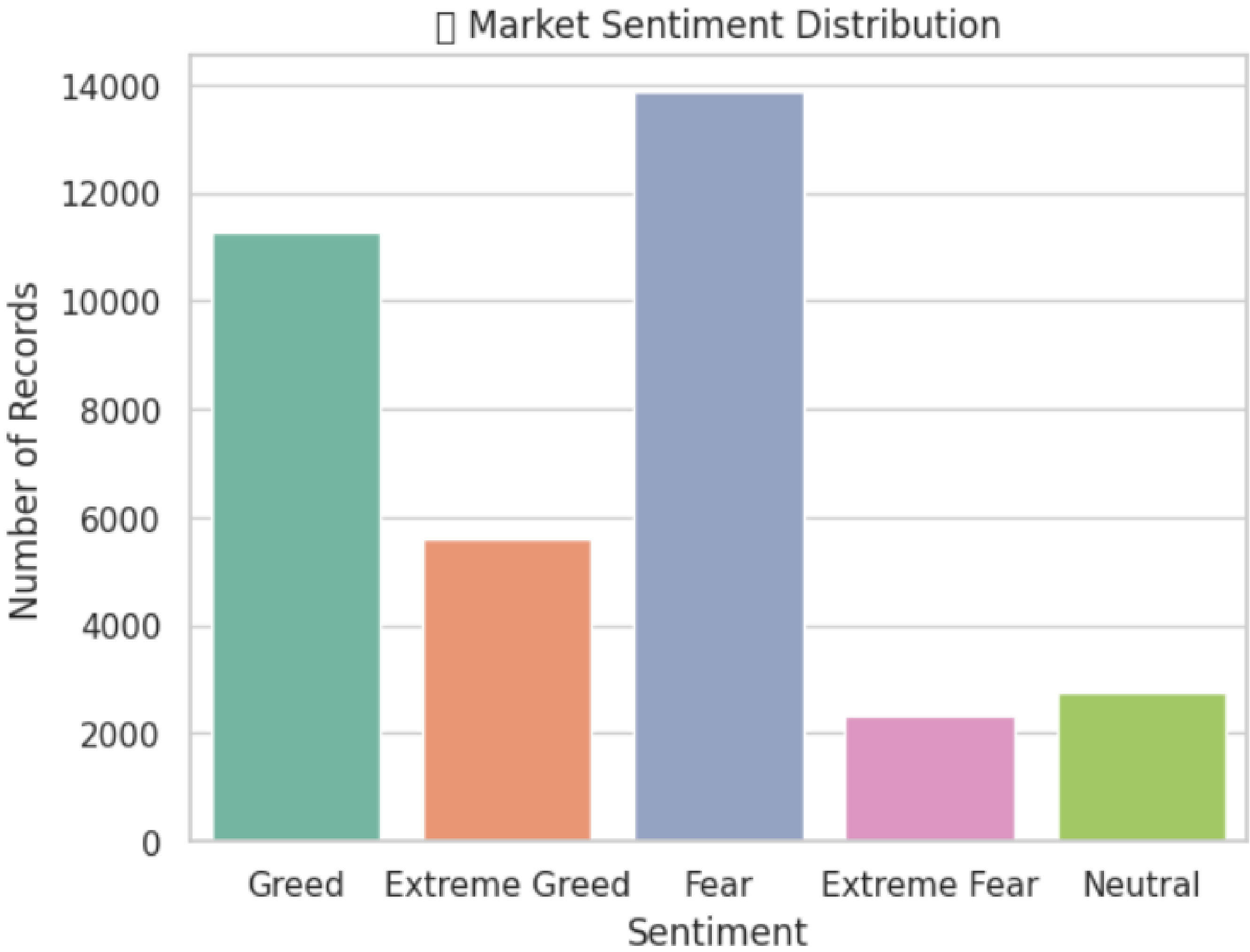
1. Contains trade-level information from Hyperliquid such as:
   Account, Execution Price, Size USD, Side, Closed PnL, Timestamp IST, etc.
2. Captures individual trading behavior (profitability, volume, risk)
3. [Download from Google Drive]()

2. Market Sentiment (Fear & Greed Index)

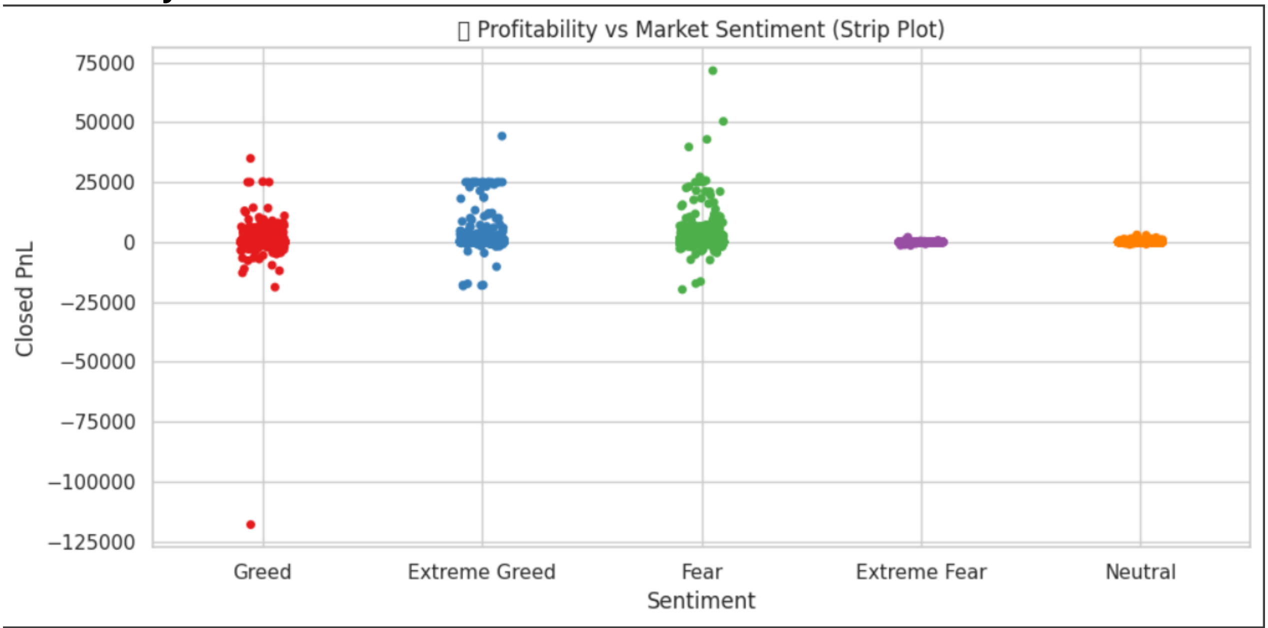
1. Includes daily market sentiment classification as one of: Extreme Fear, Fear, Neutral, Greed, or Extreme Greed
2. Used to label trades by emotional market context
3. [Download from Google Drive]

Output Plot:

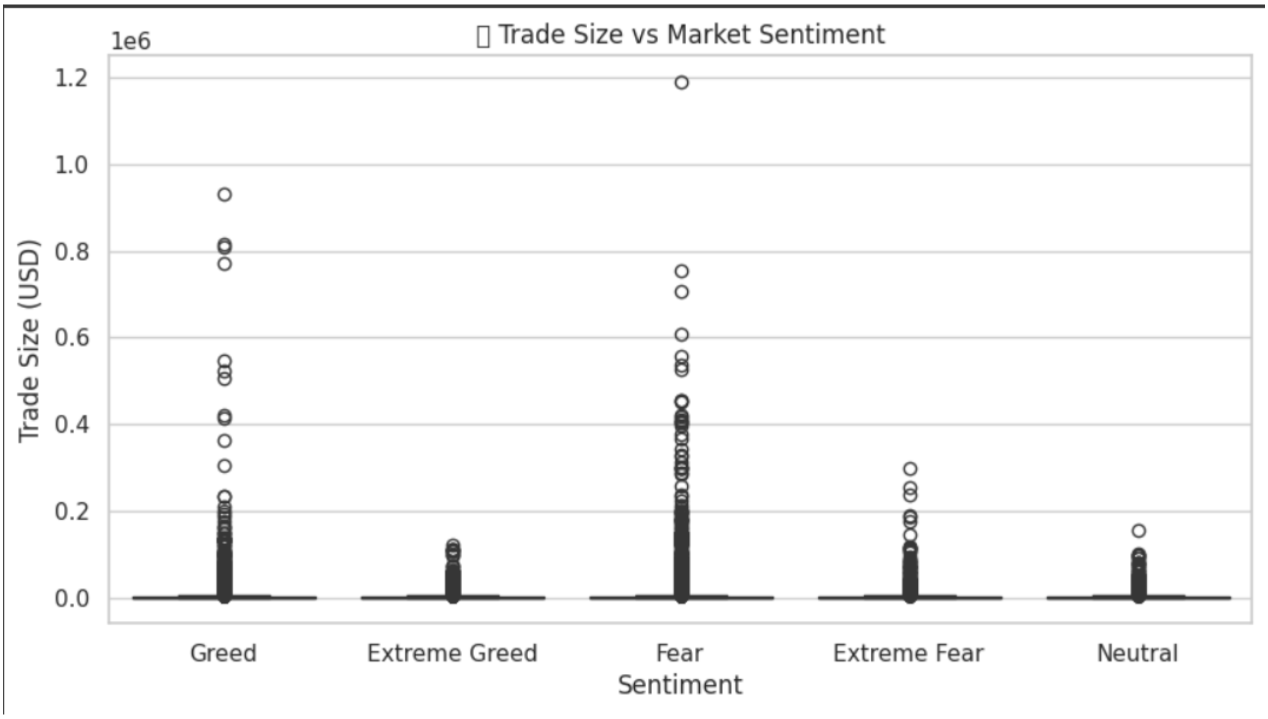
1. **Sentiment Distribution:**



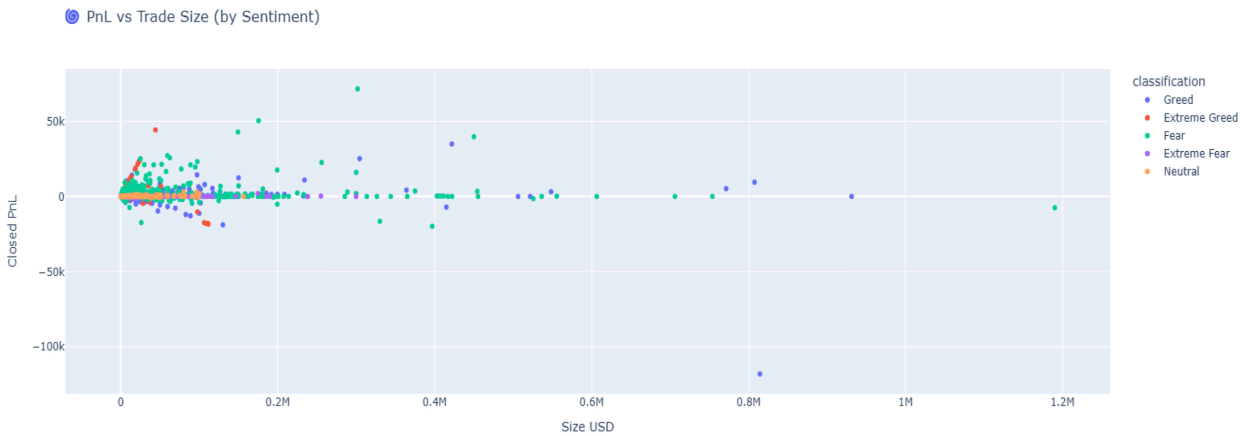
2. **Profitability vs Market Sentiment:**



3. Trade Size vs Sentiment:



4. PnL vs Trade Size Scatter Plot:



Inference:

This exploratory data analysis revealed a strong correlation between market sentiment (as measured by the Fear & Greed Index) and trader behavior. The following key conclusions were drawn:

Sentiment Affects Trade Size:

- On days classified as "Greed", traders tend to place larger trades, showing increased risk appetite.
- In contrast, during "Fear", trade sizes are generally smaller, indicating cautious behavior.

Sentiment Impacts Profitability:

- "Greed" days are associated with more volatile and sometimes higher profits, but also higher risk.
- "Fear" days often result in lower and more consistent PnL, suggesting traders focus on capital preservation.

Strategic Insight:

- Traders may benefit from adjusting position sizes and risk levels based on daily sentiment.

- This insight can also guide algorithmic trading strategies or human decision-making to align with prevailing market emotions.

Data Quality & Coverage:

- The analysis was conducted on valid overlapping dates between sentiment and trading data, ensuring relevance and accuracy of insights.

What I Learned from This Project:

Through this project, I learned how market sentiment plays a critical role in shaping trader behavior. By integrating data from the Fear & Greed Index with actual trading performance, I could clearly see how emotions like fear and greed influence decision-making — from trade size to profitability outcomes.

I also strengthened my skills in:

- Data cleaning and merging multiple real-world datasets with different formats
- Performing EDA (Exploratory Data Analysis) using both static (Seaborn/Matplotlib) and interactive (Plotly) charts
- Understanding how to draw meaningful business insights from numerical data
- Communicating results visually and effectively through charts and summaries

Most importantly, I learned how to **translate data patterns into actionable insights** — for example, recommending that traders adjust risk levels based on sentiment conditions. This shows the true value of data science: turning raw numbers into strategic decisions.