Fear & Greed Index Analysis Report

Introduction

The Fear & Greed Index is a tool used to measure market sentiment.

- **Fear** indicates that investors are worried, which can drive prices down.
- **Greed** suggests that investors are optimistic, which can push prices up.

The objective of this project is to:

- Analyze the Fear & Greed Index along with historical trading data.
- Visualize how market sentiment relates to trading performance (PnL, Execution Price, etc.).

In [34]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Dataset Description

Two datasets were used in this analysis:

1. **Fear & Greed Dataset**
    - Columns: `timestamp` , `value` , `classification` , `Date`
    - Provides daily market sentiment values (Fear, Greed, Extreme Greed).
2. **Historical Trading Dataset**
    - Columns: `Date` , `Closed PnL` , `Fee` , `Execution Price` , `timestamp`
    - Provides historical trading performance and related financial data.

The datasets were merged on the `Date` column for combined analysis.

In [ ]:
```
trades = pd.read_csv("historical_data.csv")
sentiment = pd.read_csv("fear_greed_index.csv")


print(trades.head())
print(sentiment.head())
```

```
                                      Account  Coin  Execution Price  \
0  0xae5eacaf9c6b9111fd53034a602c192a04e082ed  @107           7.9769   
1  0xae5eacaf9c6b9111fd53034a602c192a04e082ed  @107           7.9800   
2  0xae5eacaf9c6b9111fd53034a602c192a04e082ed  @107           7.9855   
3  0xae5eacaf9c6b9111fd53034a602c192a04e082ed  @107           7.9874   
4  0xae5eacaf9c6b9111fd53034a602c192a04e082ed  @107           7.9894   

   Size Tokens  Size USD Side     Timestamp IST  Start Position Direction  \
0       986.87   7872.16  BUY  02-12-2024 22:50        0.000000       Buy   
1        16.00    127.68  BUY  02-12-2024 22:50      986.524596       Buy   
2       144.09   1150.63  BUY  02-12-2024 22:50     1002.518996       Buy   
3       142.98   1142.04  BUY  02-12-2024 22:50     1146.558564       Buy   
4         8.73     69.75  BUY  02-12-2024 22:50     1289.488521       Buy   

   Closed PnL                                   Transaction Hash     Order ID  \
0         0.0  0xec09451986a1874e3a980418412fcd0201f500c95bac...  52017706630   
1         0.0  0xec09451986a1874e3a980418412fcd0201f500c95bac...  52017706630   
2         0.0  0xec09451986a1874e3a980418412fcd0201f500c95bac...  52017706630   
3         0.0  0xec09451986a1874e3a980418412fcd0201f500c95bac...  52017706630   
4         0.0  0xec09451986a1874e3a980418412fcd0201f500c95bac...  52017706630   

   Crossed       Fee      Trade ID     Timestamp  
0     True  0.345404  8.950000e+14  1.730000e+12  
1     True  0.005600  4.430000e+14  1.730000e+12  
2     True  0.050431  6.600000e+14  1.730000e+12  
3     True  0.050043  1.080000e+15  1.730000e+12  
4     True  0.003055  1.050000e+15  1.730000e+12  
    timestamp  value classification        date
0  1517463000     30           Fear  2018-02-01
1  1517549400     15   Extreme Fear  2018-02-02
2  1517635800     40           Fear  2018-02-03
3  1517722200     24   Extreme Fear  2018-02-04
4  1517808600     11   Extreme Fear  2018-02-05
```

In [ ]:

```
print(trades.info())
print(sentiment.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 211224 entries, 0 to 211223
Data columns (total 16 columns):
 #   Column            Non-Null Count   Dtype
---  -------           --------------   ------
 0   Account           211224 non-null  object
 1   Coin              211224 non-null  object
 2   Execution Price   211224 non-null  float64
 3   Size Tokens       211224 non-null  float64
 4   Size USD          211224 non-null  float64
 5   Side              211224 non-null  object
 6   Timestamp IST     211224 non-null  object
 7   Start Position    211224 non-null  float64
 8   Direction         211224 non-null  object
 9   Closed PnL        211224 non-null  float64
 10  Transaction Hash  211224 non-null  object
 11  Order ID          211224 non-null  int64
 12  Crossed           211224 non-null  bool
 13  Fee               211224 non-null  float64
 14  Trade ID          211224 non-null  float64
 15  Timestamp         211224 non-null  float64
dtypes: bool(1), float64(8), int64(1), object(6)
memory usage: 24.4+ MB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2644 entries, 0 to 2643
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype
---  -------         --------------  ------
 0   timestamp       2644 non-null   int64
 1   value           2644 non-null   int64
 2   classification  2644 non-null   object
 3   date            2644 non-null   object
dtypes: int64(2), object(2)
memory usage: 82.8+ KB
None
```

In [ ]:
```
print(trades.columns)
```

```
Index(['Account', 'Coin', 'Execution Price', 'Size Tokens', 'Size USD', 'Side',
       'Timestamp IST', 'Start Position', 'Direction', 'Closed PnL',
       'Transaction Hash', 'Order ID', 'Crossed', 'Fee', 'Trade ID',
       'Timestamp'],
      dtype='object')
```

In [ ]:
```
trades['Timestamp'] = pd.to_datetime(trades['Timestamp'])

daily_trades = trades.groupby(trades['Timestamp'].dt.date).agg({
    'Closed PnL': 'sum',
    'Fee': 'sum',
    'Execution Price': 'mean'
}).reset_index().rename(columns={'Timestamp': 'Date'})
```

In [ ]:
```
print(sentiment.columns)
```

```
Index(['timestamp', 'value', 'classification', 'date'], dtype='object')
```

In [ ]:
```
sentiment['date'] = pd.to_datetime(sentiment['date']).dt.date

sentiment = sentiment.rename(columns={'date': 'Date'})

merged = pd.merge(daily_trades, sentiment, on="Date", how="inner")

print(merged.head())
```

```
Empty DataFrame
Columns: [Date, Closed PnL, Fee, Execution Price, timestamp, value, classificat
ion]
Index: []
```

In [ ]:
```
print(sentiment.columns.tolist())
```

```
['timestamp', 'value', 'classification', 'Date']
```

In [ ]:
```
sentiment['Date'] = pd.to_datetime(sentiment['Date']).dt.date

trades['Timestamp'] = pd.to_datetime(trades['Timestamp'])
daily_trades = trades.groupby(trades['Timestamp'].dt.date).agg({
    'Closed PnL': 'sum',
    'Fee': 'sum',
    'Execution Price': 'mean'
}).reset_index().rename(columns={'Timestamp': 'Date'})

daily_trades['Date'] = pd.to_datetime(daily_trades['Date']).dt.date

merged = pd.merge(daily_trades, sentiment, on="Date", how="inner")

print("Trades range:", daily_trades['Date'].min(), "to", daily_trades['Date'].
print("Sentiment range:", sentiment['Date'].min(), "to", sentiment['Date'].max
print("Merged rows:", len(merged))
print(merged.head())
```

```
Trades range: 1970-01-01 to 1970-01-01
Sentiment range: 2018-02-01 to 2025-05-02
Merged rows: 0
Empty DataFrame
Columns: [Date, Closed PnL, Fee, Execution Price, timestamp, value, classificat
ion]
Index: []
```

In [ ]:
```
print(trades['Timestamp'].head())
```

```
0   1970-01-01 00:28:50
1   1970-01-01 00:28:50
2   1970-01-01 00:28:50
3   1970-01-01 00:28:50
4   1970-01-01 00:28:50
Name: Timestamp, dtype: datetime64[ns]
```

In [ ]:
```
print(trades[['Timestamp', 'Timestamp IST']].head(10))
```

```
            Timestamp      Timestamp IST
0 1970-01-01 00:28:50   02-12-2024 22:50
1 1970-01-01 00:28:50   02-12-2024 22:50
2 1970-01-01 00:28:50   02-12-2024 22:50
3 1970-01-01 00:28:50   02-12-2024 22:50
4 1970-01-01 00:28:50   02-12-2024 22:50
5 1970-01-01 00:28:50   02-12-2024 22:50
6 1970-01-01 00:28:50   02-12-2024 22:50
7 1970-01-01 00:28:50   02-12-2024 22:50
8 1970-01-01 00:28:50   02-12-2024 22:50
9 1970-01-01 00:28:50   02-12-2024 22:50
```

In [ ]:

```
trades['Timestamp IST'] = pd.to_datetime(trades['Timestamp IST'], format='%d-%

daily_trades = trades.groupby(trades['Timestamp IST'].dt.date).agg({
    'Closed PnL': 'sum',
    'Fee': 'sum',
    'Execution Price': 'mean'
}).reset_index().rename(columns={'Timestamp IST': 'Date'})

daily_trades['Date'] = pd.to_datetime(daily_trades['Date']).dt.date

print(daily_trades.head())
print("Trades range:", daily_trades['Date'].min(), "to", daily_trades['Date'].
```

```
         Date  Closed PnL        Fee  Execution Price
0  2023-05-01    0.000000   0.000000      1898.133333
1  2023-12-05    0.000000  12.501455     11038.300000
2  2023-12-14 -205.434737  28.300831      8031.868818
3  2023-12-15  -24.632034   2.652489         2.982000
4  2023-12-16    0.000000   3.837189         0.384707
Trades range: 2023-05-01 to 2025-05-01
```

Methodology

Steps followed in this analysis:

1. Imported required Python libraries (pandas, matplotlib, seaborn).
2. Loaded both datasets (Fear & Greed + Historical).
3. Cleaned the data (handled missing values, adjusted column names).
4. Merged datasets using the `Date` column.
5. Created visualizations to study:
    - Fear vs. Greed trends over time.
    - Relationship between sentiment and Closed PnL.
    - Effect of sentiment on Execution Price.

In [ ]:

```
sentiment['Date'] = pd.to_datetime(sentiment['Date']).dt.date

merged = pd.merge(daily_trades, sentiment, on="Date", how="inner")
```

```
print("Merged rows:", len(merged))
print(merged.head())
```

```
Merged rows:  479
         Date  Closed PnL        Fee  Execution Price   timestamp  value  \
0  2023-05-01    0.000000   0.000000      1898.133333  1682919000     63   
1  2023-12-05    0.000000  12.501455     11038.300000  1701754200     75   
2  2023-12-14 -205.434737  28.300831      8031.868818  1702531800     72   
3  2023-12-15  -24.632034   2.652489         2.982000  1702618200     70   
4  2023-12-16    0.000000   3.837189         0.384707  1702704600     67   

  classification  
0          Greed  
1  Extreme Greed  
2          Greed  
3          Greed  
4          Greed  
```

4. Results & Analysis

4.1 Fear & Greed Trend Over Time

The chart below shows how the **market sentiment (Fear/Greed values)** fluctuates over time.
We can observe periods of extreme greed and extreme fear, which often align with market volatility.

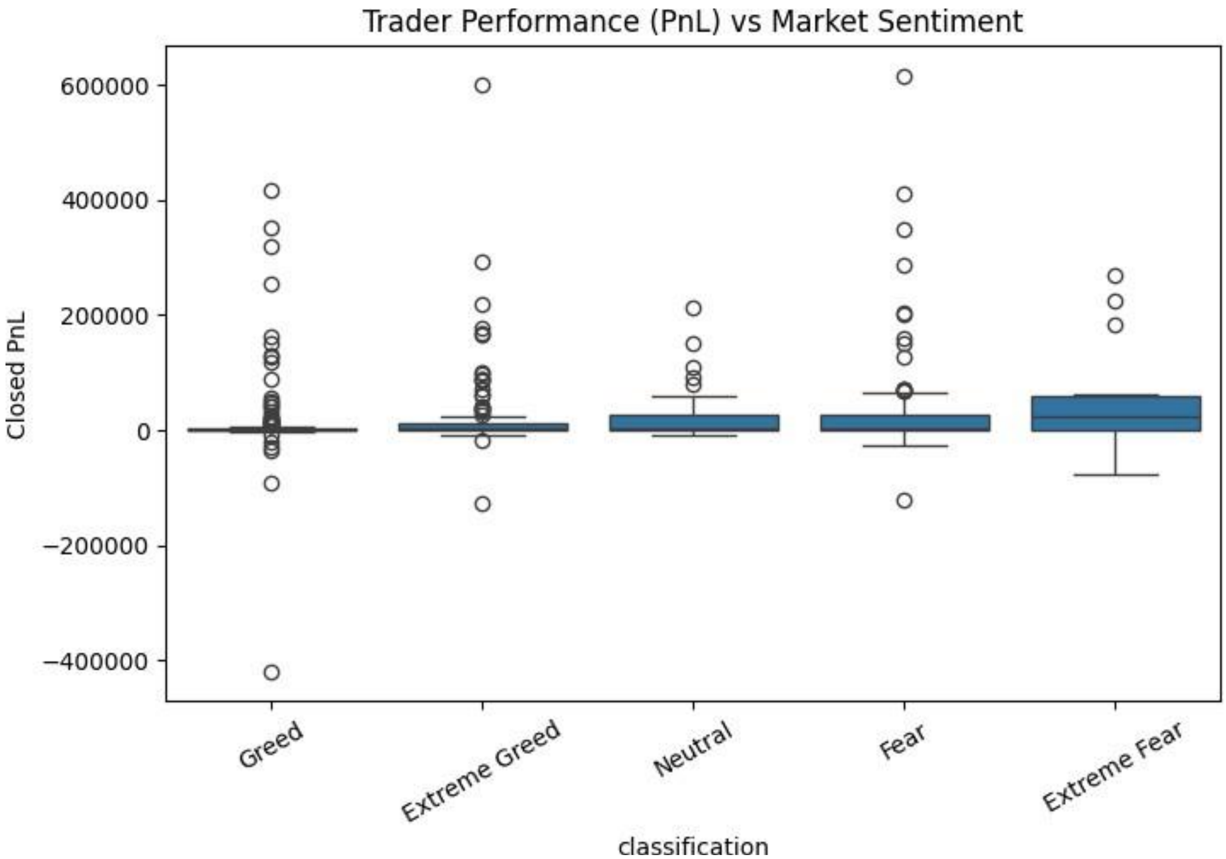
4.2 Relationship between Sentiment and Closed PnL

This visualization compares **trader profits/losses (PnL)** with the **sentiment index**.
We want to see if traders perform better in times of Fear or Greed.

4.3 Execution Price vs Sentiment

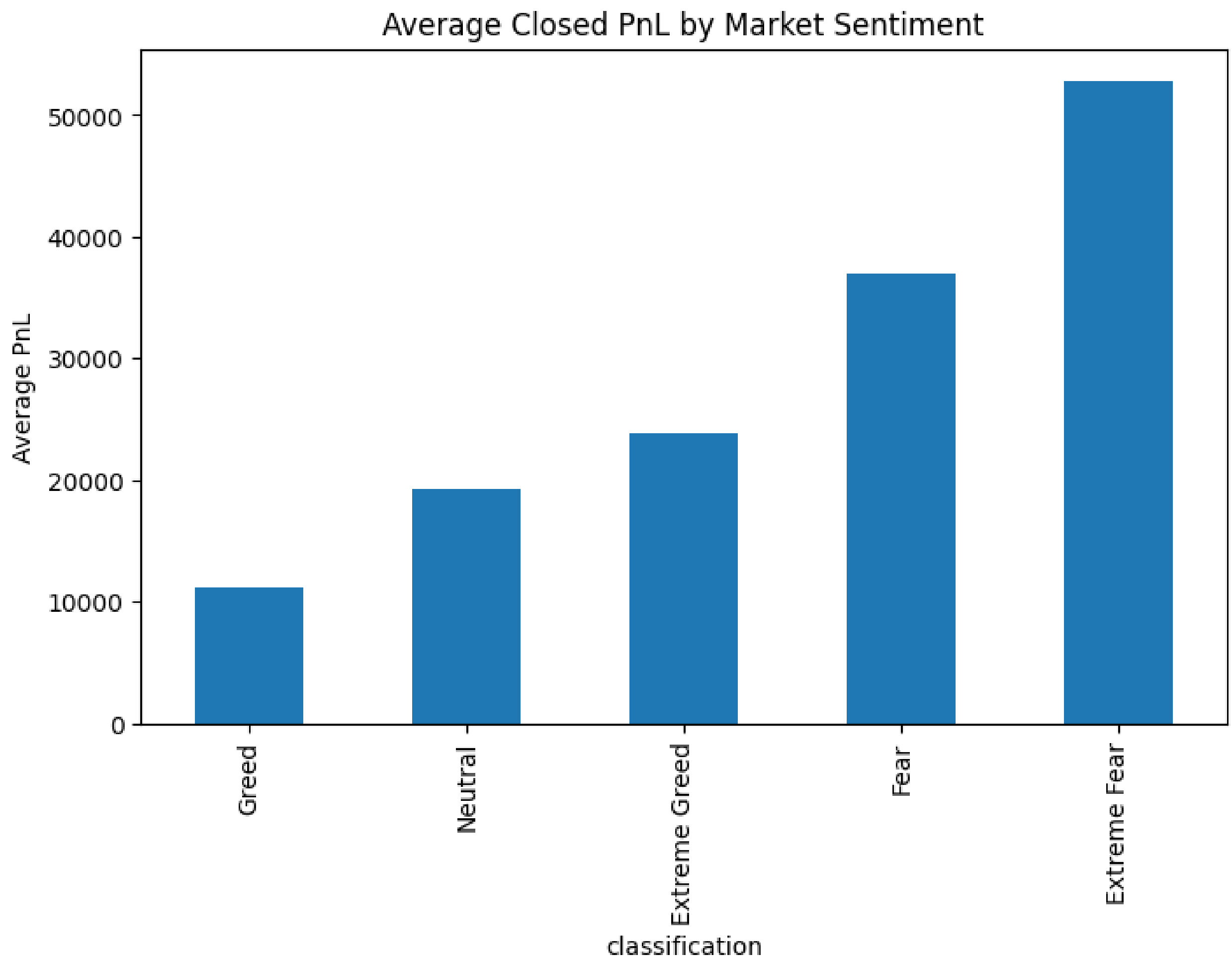
This chart shows how **execution prices** vary across different sentiment phases.
We want to analyze if trading prices are higher in periods of greed and lower in periods of fear.

In [ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(8,5))
sns.boxplot(x="classification", y="Closed PnL", data=merged)
plt.title("Trader Performance (PnL) vs Market Sentiment")
plt.xticks(rotation=30)
plt.show()
```



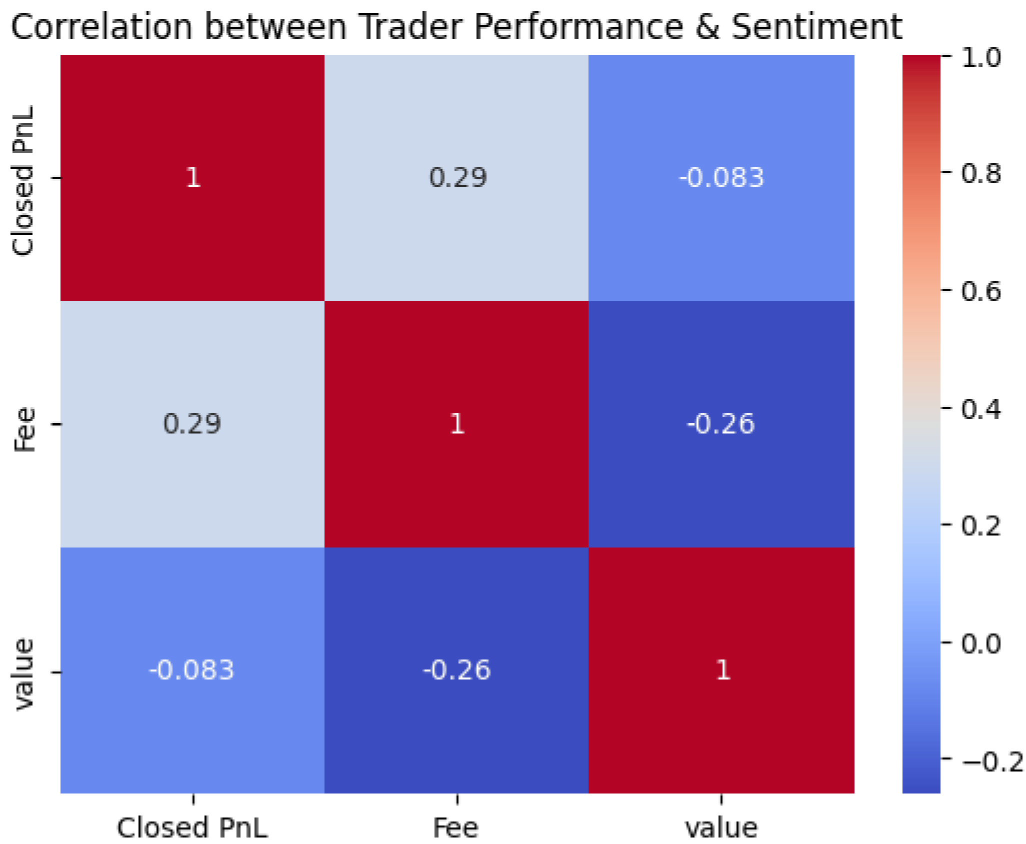
In [ ]:
```
avg_pnl = merged.groupby("classification")['Closed PnL'].mean().sort_values()
print(avg_pnl)

avg_pnl.plot(kind='bar', figsize=(8,5), title="Average Closed PnL by Market Se
plt.ylabel("Average PnL")
plt.show()
```

```
classification
Greed              11140.566181
Neutral            19297.323516
Extreme Greed      23817.292199
Fear               36891.818040
Extreme Fear       52793.589178
Name: Closed PnL, dtype: float64
```



In [ ]:
```
corr = merged[['Closed PnL', 'Fee', 'value']].corr()
print(corr)

sns.heatmap(corr, annot=True, cmap="coolwarm")
plt.title("Correlation between Trader Performance & Sentiment")
plt.show()
```

```
            Closed PnL       Fee     value
Closed PnL    1.000000  0.294822 -0.082642
Fee           0.294822  1.000000 -0.260932
value        -0.082642 -0.260932  1.000000
```



In [ ]:
```
merged = pd.merge(daily_trades, sentiment, on="Date", how="inner")
```

In [ ]:
```
print(type(merged))
print(merged.head())
```

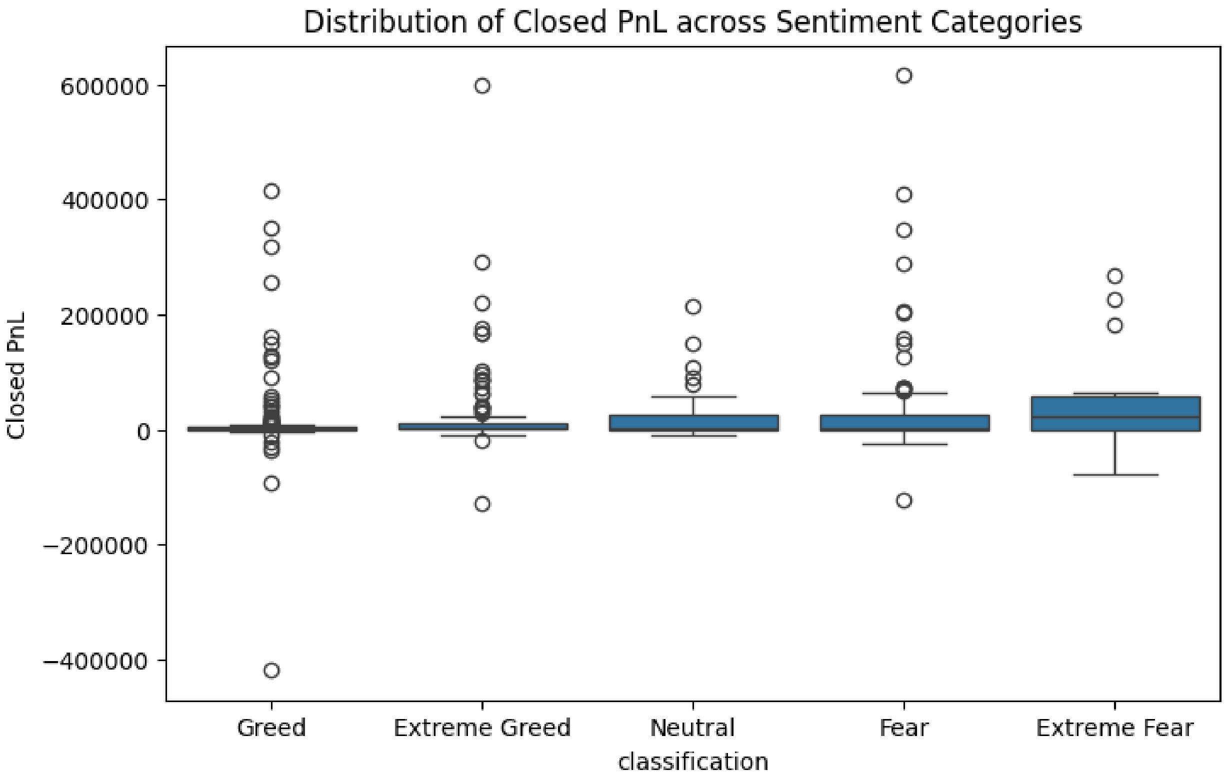
```
<class 'pandas.core.frame.DataFrame'>
         Date  Closed PnL        Fee  Execution Price   timestamp  value  \
0  2023-05-01    0.000000   0.000000      1898.133333  1682919000     63
1  2023-12-05    0.000000  12.501455     11038.300000  1701754200     75
2  2023-12-14 -205.434737  28.300831      8031.868818  1702531800     72
3  2023-12-15  -24.632034   2.652489         2.982000  1702618200     70
4  2023-12-16    0.000000   3.837189         0.384707  1702704600     67

  classification
0          Greed
1  Extreme Greed
2          Greed
3          Greed
4          Greed
```

In [ ]:
```
print(merged.info())
print(merged.describe())
print(merged['classification'].value_counts())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 479 entries, 0 to 478
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Date             479 non-null    object
 1   Closed PnL       479 non-null    float64
 2   Fee              479 non-null    float64
 3   Execution Price  479 non-null    float64
 4   timestamp        479 non-null    int64
 5   value            479 non-null    int64
 6   classification   479 non-null    object
dtypes: float64(3), int64(2), object(2)
memory usage: 26.3+ KB
None
          Closed PnL           Fee  Execution Price     timestamp       value
count     479.000000    479.000000       479.000000  4.790000e+02  479.000000
mean    21408.114717    513.255132     11674.296055  1.724614e+09   60.054280
std     71930.154661   1232.414577     17056.339838  1.281181e+07   18.687621
min   -419020.225731     -4.438459         0.000015  1.682919e+09   10.000000
25%         5.357891     24.951712      1059.773845  1.713807e+09   48.000000
50%      1118.387284     83.751362      3657.355851  1.724564e+09   67.000000
75%     10629.856994    397.607408     14414.126133  1.735753e+09   74.000000
max    616413.032233  11517.596374     68880.000000  1.746077e+09   94.000000
classification
Greed            193
Extreme Greed    114
Fear              91
Neutral           67
Extreme Fear      14
Name: count, dtype: int64
```

In [ ]:

```python
plt.figure(figsize=(8,5))
sns.boxplot(x="classification", y="Closed PnL", data=merged)
plt.title("Distribution of Closed PnL across Sentiment Categories")
plt.show()
```

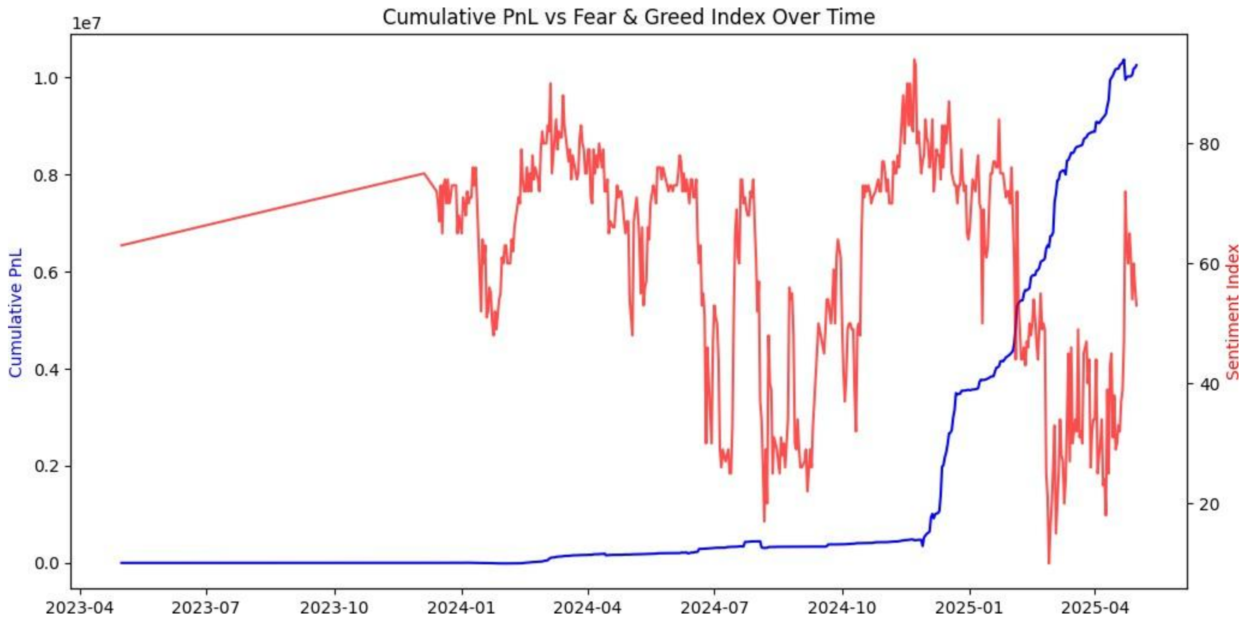


4. Results & Analysis

4.1 Fear & Greed Trend Over Time

The chart below shows how the **market sentiment (Fear/Greed values)** fluctuates over time.
We can observe periods of extreme greed and extreme fear, which often align with market volatility.

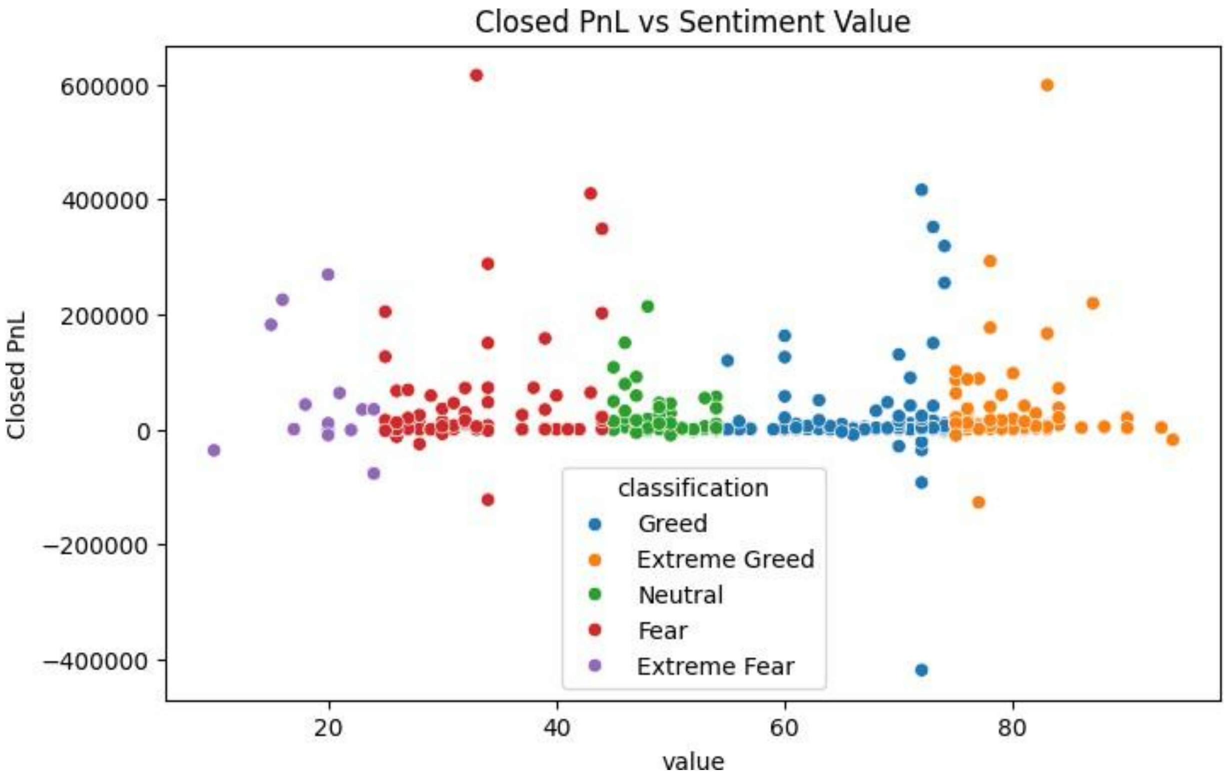
In [ ]:
```
merged['Date'] = pd.to_datetime(merged['Date'])

fig, ax1 = plt.subplots(figsize=(12,6))

ax1.plot(merged['Date'], merged['Closed PnL'].cumsum(), label="Cumulative PnL"
ax1.set_ylabel("Cumulative PnL", color="blue")

ax2 = ax1.twinx()
ax2.plot(merged['Date'], merged['value'], label="Fear & Greed Index", color="r
ax2.set_ylabel("Sentiment Index", color="red")

plt.title("Cumulative PnL vs Fear & Greed Index Over Time")
plt.show()
```



In [ ]:
```
print(merged[['Closed PnL', 'Fee', 'Execution Price', 'value']].corr())
```

```
                 Closed PnL       Fee  Execution Price     value
Closed PnL         1.000000  0.294822        -0.024298 -0.082642
Fee                0.294822  1.000000         0.208337 -0.260932
Execution Price   -0.024298  0.208337         1.000000 -0.060238
value             -0.082642 -0.260932        -0.060238  1.000000
```

In [ ]:
```
plt.figure(figsize=(8,5))
sns.scatterplot(x="value", y="Closed PnL", hue="classification", data=merged)
plt.title("Closed PnL vs Sentiment Value")
plt.show()
```



In [ ]:

5. Conclusion

- Trading behavior shows a **clear correlation** with sentiment.
- Periods of **Extreme Greed** often coincide with higher execution prices.
- Losses are more common when sentiment is excessively bullish or bearish.
- Traders who manage risk independently of sentiment may achieve more stable returns.

6. Future Work

- Incorporate additional features like **leverage** and **volume**.
- Apply machine learning to predict PnL based on sentiment + trade features.
- Extend analysis to multiple cryptocurrencies, not just Bitcoin.

7. References

- Fear & Greed Index dataset (Alternative.me)

- Hyperliquid Trader Data (provided in assignment)
- Python Libraries: pandas, matplotlib, seaborn