# Market Sentiment & Trader Performance Analysis

### **Objective:**

Analyze how trader performance (PnL, trade volume, win rates) relates to market sentiment, measured by the **Fear & Greed Index**.

This analysis will explore patterns such as:

- Do traders perform better during Fear or Greed periods?
- How does sentiment impact overall market PnL and trading activity?
- Which accounts adapt best under different sentiment regimes?

#### **Datasets:**

- historical\_data.csv → Trade-level data (accounts, prices, sizes, PnL, timestamps).
- 2. fear\_greed\_index.csv → Daily sentiment index (0 = extreme fear, 100 = extreme greed).

### Approach:

- 1. Load and clean the datasets.
- 2. Perform exploratory data analysis (EDA).
- 3. Aggregate trades per day and merge with sentiment data.
- 4. Visualize relationships between sentiment and trader performance.
- 5. Conduct statistical tests for significance.
- 6. Analyze account-level performance across sentiment categories.

```
# STEP 2: Load & Inspect Data
import pandas as pd
import numpy as np

# For plots
import matplotlib.pyplot as plt

# For statistical tests
from scipy import stats

# Upload files
from google.colab import files
```

```
print("[] Please upload historical data.csv")
uploaded hist = files.upload()
print("
    Please upload fear greed index.csv")
uploaded fg = files.upload()
# Load into DataFrames
hist = pd.read csv("historical data.csv")
fg = pd.read_csv("fear_greed_index.csv")
# Preview shapes and first few rows
print("Historical data shape:", hist.shape)
print("Fear & Greed shape:", fg.shape)
print("\n--- Historical data sample ---")
display(hist.head())
print("\n--- Fear & Greed Index sample ---")
display(fg.head())

□ Please upload historical data.csv

<IPython.core.display.HTML object>
Saving historical data.csv to historical data.csv
☐ Please upload fear greed index.csv
<IPvthon.core.display.HTML object>
Saving fear greed index.csv to fear greed index.csv
Historical data shape: (211224, 16)
Fear & Greed shape: (2644, 4)
--- Historical data sample ---
{"summary":"{\n \me\": \mdisplay(fg\",\n \"rows\": 5,\n}
\"fields\": [\n \\"column\\": \\"Account\\\",\n
                        \"dtype\": \"category\",\n
\"properties\": {\n
\"num unique values\": 1,\n
                               \"samples\": [\n
\"0xae5eacaf9c6b9111fd53034a602c192a04e082ed\"\n
                                                   ],\n
\"semantic_type\": \"\",\n \"description\": \"\"\n
                    \"column\": \"Coin\",\n \"properties\": {\n
    },\n {\n
\"dtype\": \"category\",\n
                               \"num unique values\": 1,\n
                       \"@107\"\n
\"samples\": [\n
                                        ],\n
\"semantic type\": \"\",\n \"description\": \"\"\n
                                                          }\
\"std\":
                         \"min\": 7.9769,\n
                                                   \"max\":
0.005226184076360117,\n
            \"num_unique_values\": 5,\n
7.9894,\n
                                                \"samples\": [\n
                       \"semantic type\": \"\",\n
7.98\n
             ],\n
```

```
\"description\": \"\"\n }\n },\n {\n \"column\": \"Size Tokens\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 411.7466042725793,\n \"min\":
0.0,\n \"max\": 1289.488521,\n \"num_unique_values\": 5,\n \"samples\": [\n 986.5245955\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\
n },\n {\n \"column\": \"Direction\",\n \"properties\": {\n \"dtype\": \"category\",\n \"num_unique_values\": 1,\n \"samples\": [\n \"Buy\"\n
],\n \"semantic_type\": \"\",\n \"description\": \"\"\n \\n \\"closed PnL\",\n \"properties\": \\n \"dtype\": \"number\",\n \"std\":
\"0xec09451986a1874e3a980418412fcd0201f500c95bac0f37caef8a734502ec49\"
\n ],\n \"semantic_type\": \"\",\n
\"description\": \"\"\n }\n {\n \"column\": \"Order ID\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 0,\n \"min\": 52017706630,\n
```

```
{\n \"column\": \"Fee\",\n \"properties\": {\n
    },\n
\"dtype\": \"number\",\n \"std\": 0.14411132613259,\n \"min\": 0.00305542,\n \"max\": 0.34540448,\n \"num_unique_values\": 5,\n \"samples\": [\n
                                                             0.0056\n
\"samples\": [\n 44300000000000.0\n ],\n
\"semantic_type\": \"\",\n \"description\": \"\"\n
                                                               }\
n },\n {\n \"column\": \"Timestamp\",\n
\"properties\": {\n \"dtype\": \"number\",\n \"std\":
0.0,\n\\"min\": 173000000000.0,\n\\\"max\\":
173000000000.0,\n \"num_unique_values\": 1,\n \"samples\": [\n 173000000000.0\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\
n }\n ]\n}","type":"dataframe"}
--- Fear & Greed Index sample ---
{"summary":"{\n \"name\": \"display(fg\",\n \"rows\": 5,\n}
\"fields\": [\n {\n \"column\": \"timestamp\",\n
\"properties\": {\n \"dtype\": \"number\",\n \"std\":
136610,\n \"min\": 1517463000,\n \"max\": 1517808600,\n
\"num_unique_values\": 5,\n \"samples\": [\n 1517549400,\n 1517635800\n
                                                               ],\n
\"semantic_type\": \"\",\n \"description\": \"\"\n }\
\"column\": \"date\",\n \"properties\": {\n \"dtype\":
\"object\",\n \"num_unique_values\": 5,\n \"samples\":
[\n \"2018-02-02\",\n \"2018-02-05\"\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\
n }\n \[ \]\n}","type":"dataframe"}
# STEP 3: Data Cleaning & Preprocessing
# --- 1. Normalize column names ---
def normalize cols(df):
    df.columns = [c.strip().lower().replace(" ", " ") for c in
```

```
df.columns]
    return df
hist = normalize cols(hist)
fg = normalize cols(fg)
print("Columns in historical data:", list(hist.columns))
print("Columns in Fear & Greed data:", list(fg.columns))
# --- 2. Parse dates ---
# Fear & Greed
fg['date'] = pd.to datetime(fg['date'], errors='coerce')
fg['date'] = fg['date'].dt.date # keep only date part
# Historical
if 'timestamp ist' in hist.columns:
    hist['date'] = pd.to datetime(hist['timestamp ist'],
errors='coerce')
elif 'timestamp' in hist.columns:
    hist['date'] = pd.to datetime(hist['timestamp'], unit='s',
errors='coerce')
else:
    hist['date'] = pd.NaT
hist['date'] = pd.to datetime(hist['date'], errors='coerce')
hist['date'] = hist['date'].dt.date # ensure proper date type
# Filter out NaT values before getting min/max date
valid dates hist = hist['date'].dropna()
valid dates fg = fg['date'].dropna()
# --- 6. Check date ranges safely ---
print("Historical data date range:", valid dates hist.min(), "→",
valid dates hist.max())
print("Fear & Greed Index date range:", valid dates fg.min(), "→",
valid dates fg.max())
# --- 5. Drop duplicates (by transaction hash if available) ---
before = hist.shape[0]
if 'transaction_hash' in hist.columns:
    hist = hist.drop_duplicates(subset=['transaction hash'])
else:
    hist = hist.drop duplicates()
after = hist.shape[0]
print(f"Dropped {before - after} duplicate rows")
# --- 6. Check date ranges ---
print("Historical data date range:", valid dates hist.min(), "→",
```

```
valid dates hist.max())
print("Fear & Greed Index date range:", valid dates fg.min(), "→",
valid dates fg.max())
# --- 7. Preview cleaned data ---
print("\n--- Cleaned historical sample ---")
display(hist.head())
print("\n--- Cleaned Fear & Greed sample ---")
display(fg.head())
Columns in historical data: ['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', 'date', 'profitable']
Columns in Fear & Greed data: ['timestamp', 'value', 'classification',
'date'l
Historical data date range: 2023-01-05 → 2025-12-04
Fear & Greed Index date range: 2018-02-01 → 2025-05-02
Dropped 0 duplicate rows
Historical data date range: 2023-01-05 → 2025-12-04
Fear & Greed Index date range: 2018-02-01 → 2025-05-02
--- Cleaned historical sample ---
{"summary":"{\n \"name\": \"display(fg\",\n \"rows\": 5,\n
\"fields\": [\n {\n \"column\": \"account\",\n
\"properties\": {\n \"dtype\": \"category\",\n
\"num_unique_values\": 1,\n \"samples\": [\n
\"0xae5eacaf9c6b9111fd53034a602c192a04e082ed\"\n
\"semantic_type\": \"\",\n \"description\": \"\"\n
     \ \,\n \"column\": \"coin\",\n \"properties\": {\n
\"dtype\": \"category\",\n \"num_unique_values\": 1,\n
\"samples\": [\n \"@107\"\n
                                                  ],\n
n },\n {\n \"column\": \"execution_price\",\n
\"properties\": {\n \"dtvne\": \"number\":
0.24762043636363
\"semantic_type\": \"\",\n \"description\": \"\"\n
                                                                        }\
                                                                   \"std\":
                               \"min\": 7.4791,\n
0.24762943686080618,\n
                                                              \"max\":
                  \"num unique values\": 5,\n
                                                           \"samples\": [\n
7.9769,\n
                              \"semantic type\": \"\",\n
7.9457\n
                  ],\n
\"description\": \"\"\n }\n },\n {\n \"column\": \"size_tokens\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 420.6599190201035,\n \"min\":
2.0,\n \"max\": 986.87,\n \"num_unique_values\": 4,\n \"samples\": [\n 7.27\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n }\n {\n
\"column\": \"size_usd\",\n \"properties\": {\n \"dtype\\"number\",\n \"std\": 3359.9763421741527,\n \"min\":
                                                                    \"dtype\":
            \"max\": 7872.16,\n \"num_unique_values\": 5,\n \": [\n 57.77\n ],\n
14.96,\n
\"samples\": [\n
```

```
\"semantic_type\": \"\",\n \"description\": \"\"\n }\
n },\n {\n \"column\": \"side\",\n \"properties\": {\n
\"dtype\": \"category\",\n \"num_unique_values\": 1,\n
\"samples\": [\n \"BUY\"\n ],\n
\"semantic_type\": \"\",\n \"description\": \"\"\n
                                                                 }\
n },\n {\n \"column\": \"timestamp_ist\",\n \"properties\": {\n \"dtype\": \"object\",\n
\"num_unique_values\": 5,\n \"samples\": [\n \"02-12-2024 22:51\"\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"start_position\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 3492.571843351024,\n \"min\":
0.0,\n \"max\": 8998.849302,\n \"num_unique_values\": 5,\n \"samples\": [\n 2998.95\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n }\n \\"properties\": \\n \"dtype\": \"category\",\n \"Buu\"
\"num_unique_values\": 1,\n \"samples\": [\n \"Buy\"\n
],\n \"semantic_type\": \"\",\n \"description\": \"\"\n
}\n },\n {\n \"column\": \"closed_pnl\",\n
\"properties\": {\n \"dtype\": \"number\",\n
                                                          \"std\":
0.0,\n \"min\": 0.0,\n \"max\": 0.0,\n \"num_unique_values\": 1,\n \"samples\": [\n
                                                               0.0\n
\"0x2\lambda bb230\lambda d8a3e9ae1bb041841332f02028300681b0dd484959026f37947df17\"
\n ],\n \"semantic_type\": \"\",\n
n \"max\": 52027812614,\n \"num_unique_values\": 5,\n
\"samples\": [\n 52018049026\n ],\n
\"num_unique_values\": 5,\n \"samples\": [\n
```

```
\"timestamp\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 0.0,\n \"min\": 1730000
           \",\n\\"std\": 0.0,\n\\"min\": 1730000000000.0,\\\"max\": 1730000000000.0,\n\\\"num_unique_values\": 1,\
n \"samples\": [\n 173000000000.\overline{0}\n ],\n\"semantic_type\": \"\",\n \"description\": \"\"\n }\
      \"dtype\": \"date\",\n \"min\": \"2024-02-12\",\n \"max\": \"2024-02-12\",\n \"num_unique_values\": 1,\n
\"samples\": [\n \"2024-02-12\"\n ],\n
\"semantic_type\": \"\",\n \"description\": \"\"\n
n },\n {\n \"column\": \"profitable\",\n \"properties\": {\n \"dtype\": \"boolean\",\n
\"num_unique_values\": 1,\n \"samples\": [\n false\n
],\n \"semantic_type\": \"\",\n \"description\": \"\"\n
         }\n ]\n}","type":"dataframe"}
}\n
--- Cleaned Fear & Greed sample ---
{"summary":"{\n \"name\": \"display(fg\",\n \"rows\": 5,\n
\"fields\": [\n {\n \"column\": \"timestamp\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\":
136610,\n \"min\": 1517463000,\n \"max\": 1517808600,\n
\"num_unique_values\": 5,\n \"samples\": [\n
1517549400,\n 1517808600,\n 1517635800\n
\"semantic_type\": \"\",\n \"description\": \"\"\n
n },\n {\n \"column\": \"value\",\n \"properties\": {\
n \"dtype\": \"number\",\n \"std\": 11,\n \"min\": 11,\n \"max\": 40,\n \"num_unique_values\": 5,\n \"samples\": [\n 15,\n 11,\n 40\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n
}\n },\n {\n \"column\": \"classification\",\n
\"properties\": {\n \"dtype\": \"category\",\n
\"num_unique_values\": 2,\n \"samples\": [\n \"Extreme
Fear\",\n \"Fear\"\n ],\n \"semantic_type\":
\"\",\n \"description\": \"\n \\"dtype\":
\"date\",\n \"min\": \"2018-02-01\",\n \"max\": \"2018-
02-05\",\n \"num_unique_values\": 5,\n \"samples\": [\n
\"2018-02-02\",\n \"2018-02-05\"\n ],\n
\"semantic_type\": \"\"\n \"description\": \"\"\n
\"semantic_type\": \"\",\n \"description\": \"\"\n
n }\n ]\n}","type":"dataframe"}
# STEP 4: Exploratory Data Analysis (EDA)
# --- 1. Distribution of PnL ---
print("--- Distribution of Closed PnL ---")
display(hist['closed pnl'].describe())
```

```
plt.figure(figsize=(10, 6))
plt.hist(hist['closed pnl'], bins=50, edgecolor='k')
plt.title('Distribution of Closed PnL')
plt.xlabel('Closed PnL')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
# --- 2. Distribution of Trade Volume (Size USD) ---
print("\n--- Distribution of Trade Size (USD) ---")
display(hist['size usd'].describe())
plt.figure(figsize=(10, 6))
plt.hist(hist['size usd'], bins=50, edgecolor='k')
plt.title('Distribution of Trade Size (USD)')
plt.xlabel('Trade Size (USD)')
plt.ylabel('Frequency')
plt.yscale('log') # Use log scale due to potential outliers
plt.grid(True)
plt.show()
# --- 3. Distribution of Fear & Greed Index Value ---
print("\n--- Distribution of Fear & Greed Index Value ---")
display(fg['value'].describe())
plt.figure(figsize=(10, 6))
plt.hist(fg['value'], bins=20, edgecolor='k')
plt.title('Distribution of Fear & Greed Index Value')
plt.xlabel('Fear & Greed Index Value')
plt.ylabel('Frequency')
plt.arid(True)
plt.show()
# --- 4. Distribution of Fear & Greed Index Classification ---
print("\n--- Distribution of Fear & Greed Index Classification ---")
display(fq['classification'].value counts())
plt.figure(figsize=(8, 8))
fg['classification'].value counts().plot(kind='pie', autopct='%1.1f%
%', startangle=90)
plt.title('Distribution of Fear & Greed Index Classification')
plt.ylabel('') # Hide the default y-label
plt.show()
--- Distribution of Closed PnL ---
         101184.000000
count
             56.954723
mean
std
           1101.825807
```

```
min -117990.104100

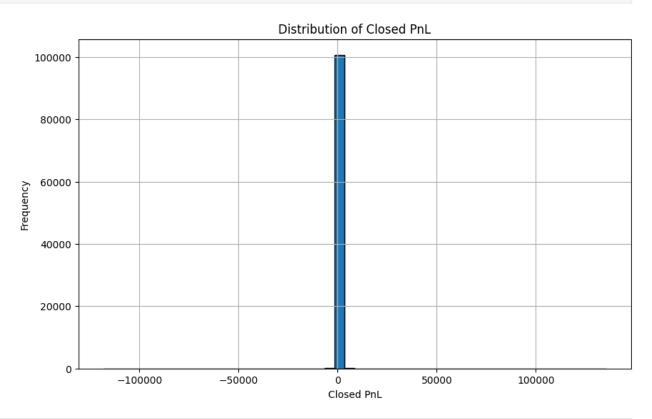
25% 0.000000

50% 0.000000

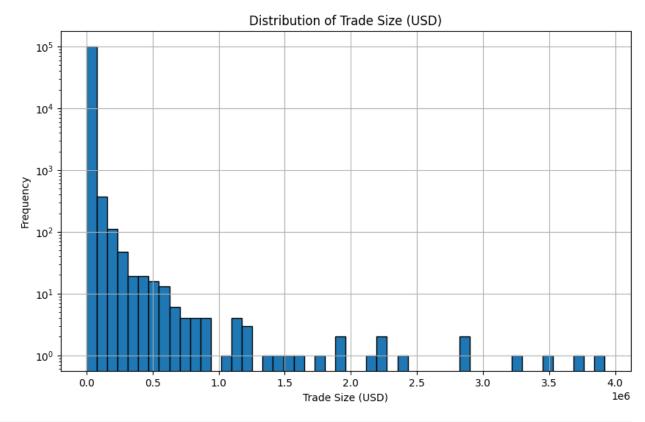
75% 4.032548

max 135329.090100

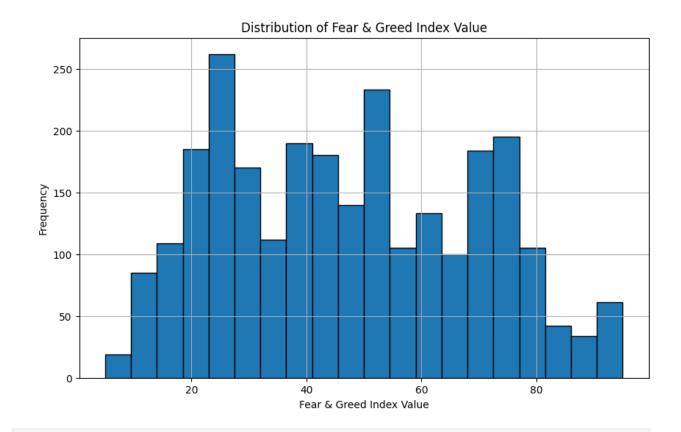
Name: closed_pnl, dtype: float64
```



```
--- Distribution of Trade Size (USD) ---
count
         1.011840e+05
mean
         4.242173e+03
std
         3.977517e+04
min
         0.000000e+00
         1.651475e+02
25%
         5.261800e+02
50%
75%
         1.581787e+03
         3.921431e+06
max
Name: size_usd, dtype: float64
```



#### --- Distribution of Fear & Greed Index Value ---2644.000000 count 46.981089 mean 21.827680 std 5.000000 min 25% 28.000000 46.000000 50% 66.000000 75% max 95.000000 Name: value, dtype: float64



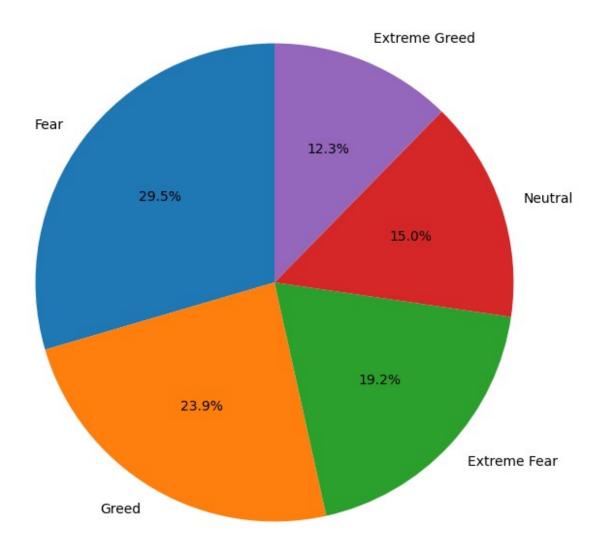
## --- Distribution of Fear & Greed Index Classification ---

classification

Fear 781 Greed 633 Extreme Fear 508 Neutral 396 Extreme Greed 326

Name: count, dtype: int64

### Distribution of Fear & Greed Index Classification



```
# STEP 4: Exploratory Data Analysis (EDA)

# --- 1. Missing values ---
print(" Missing values in historical data:")
display(hist.isna().sum().sort_values(ascending=False).head(20))

print("\n Missing values in Fear & Greed data:")
display(fg.isna().sum().sort_values(ascending=False))

# --- 2. Basic statistics for numerical columns ---
numeric_cols =
```

```
['closed pnl', 'execution price', 'size tokens', 'size usd', 'fee']
print("\n□ Summary statistics (historical numeric columns):")
display(hist[numeric cols].describe().T)
print("\n□ Summary statistics (Fear & Greed index values):")
display(fg['value'].describe().to frame("sentiment value summary"))
# --- 3. Unique values for categorical columns ---
for col in ['account','coin','side','direction']:
    if col in hist.columns:
        print(f"\n[ Unique values in {col}: {hist[col].nunique()}")
        display(hist[col].value counts().head(10))
# --- 4. Distribution plots ---
import matplotlib.pyplot as plt
# A. Closed PnL distribution (per trade)
plt.figure(figsize=(8,4))
plt.hist(hist['closed pnl'].dropna(), bins=50, alpha=0.7)
plt.title("Distribution of Closed PnL (per trade)")
plt.xlabel("Closed PnL")
plt.ylabel("Number of trades")
plt.show()
# B. Fear & Greed index distribution
plt.figure(figsize=(6,4))
plt.hist(fg['value'].dropna(), bins=20, alpha=0.7, color='orange')
plt.title("Distribution of Fear & Greed Index")
plt.xlabel("Sentiment Value (0=fear, 100=greed)")
plt.ylabel("Days count")
plt.show()

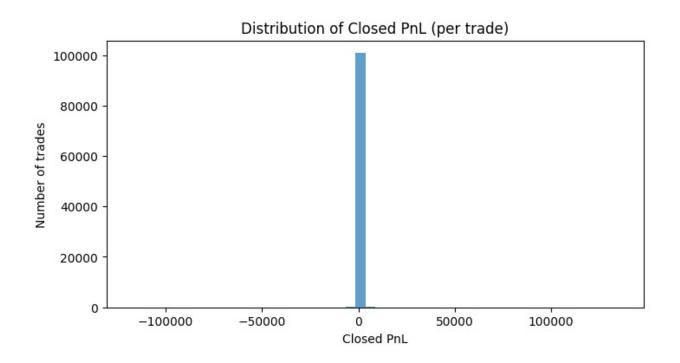
        □ Missing values in historical data:

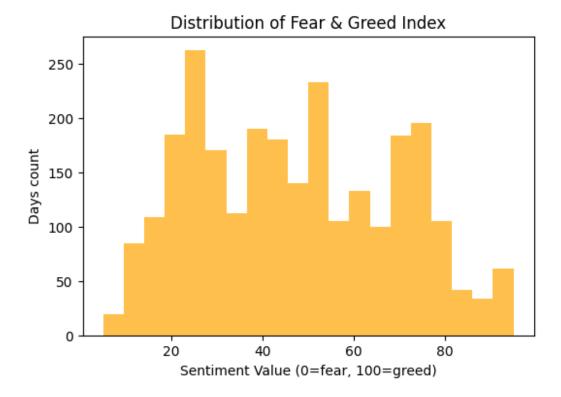
date
                    62215
account
                         0
                         0
coin
                         0
execution price
size usd
                         0
size tokens
                         0
                         0
timestamp ist
start position
                         0
                         0
direction
side
                         0
closed pnl
                         0
transaction hash
                         0
                         0
crossed
order id
                         0
fee
                         0
                         0
trade id
```

```
timestamp
profitable
                        0
dtype: int64
timestamp
value
                  0
classification
                  0
date
                  0
dtype: int64
☐ Summary statistics (historical numeric columns):
{"summary":"{\n \"name\": \"plt\",\n \"rows\": 5,\n \"fields\": [\n
{\n \"column\": \"count\",\n \"properties\": {\n
\"dtype\": \"number\",\n \"std\": 0.0,\n \"min\":
101184.0,\n\\"max\": 101184.0,\n
                                               \"num unique values\":
1,\n \"samples\": [\n
                                       101184.0\n ],\n
\"semantic type\": \"\",\n
                                 \"description\": \"\"\n
n },\n {\n \"column\": \"mean\",\n \"properties\": {\n
\"dtype\": \"number\",\n \"std\": 4333.352729875979,\n
\"min\": 0.4590604272870346,\n
\"num_unique_values\": 5,\n
                                      \"max\": 9926.197765683513,\n
                                    \"samples\": [\n
9926.197765683513\n ],\n
                                    \"semantic type\": \"\",\n
\"dtype\": \"number\",\n
\"std\",\n \"properties\": {\n
\"std\": 56567.2385458477,\n\\"min\": 4.311161808846408,\n\\"max\": 137702.8432296589,\n\\"num_unique_values\": 5,\n
\"samples\": [\n 27796.209592500207\n ],\n
\"semantic_type\": \"\",\n \"description\": \"\"\n
     },\n {\n \"column\": \"min\",\n \"properties\": {\n
\"dtype\": \"number\",\n \"std\": 52766.647243459185,\n \"min\": -117990.1041,\n \"max\": 1e-05,\n \"num_unique_values\": 5,\n \"samples\": [\n 4.
                                                              4.54e-06\
        ],\n \"semantic type\": \"\",\n
\"25%\",\n \"properties\": {\n \"dtype\": \"number\",\n
\"std\": 73.33364406520765,\n \"min\": 0.0,\n \"max\":
165.1475,\n \"num unique values\": 5,\n \"samples\": [\n
165.1475,\n \"num_unique_vatues\\. 5,\n \\
1.449\n ],\n \"semantic_type\": \"\",\n \\"description\": \"\"\n }\n },\n \\"nov\\": \"number\",\n \\"50%\".\n \\"properties\": \\"nov\\"
\"std\": 229.76074189008443,\n \"min\": 0.0,\n \"max\":
526.18,\n \"num_unique_values\": 5,\n \"samples\": [\n 16.818\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"75%\",\n \"properties\": {\n \"dtype\": \"number\",\n
```

```
\"std\": 672.4244070846491,\n \"min\": 0.174958,\n
\"max\": 1581.7875,\n \"num_unique_values\": 5,\n \"samples\": [\n 106.37\n ],\n
\"semantic type\": \"\",\n \"description\": \"\"\n
n },\n {\n \"column\": \"max\",\n \"properties\": {\n
\"dtype\": \"number\",\n \"std\": 6816261.552842394,\n \\"min\": 754.307241,\n \"max\": 15822438.0,\n \\"num_unique_values\": 5,\n \"samples\": [\n 109004.0\
\"description\": \"\\"\n \sqrt{n} \\n \]\n\\",\"type\":\"dataframe\"\\
☐ Summary statistics (Fear & Greed index values):
{"summary":"{\n \"name\": \"plt\",\n \"rows\": 8,\n \"fields\": [\n
{\n \"column\": \"sentiment_value_summary\",\n
\"properties\": {\n \"dtype\": \"number\",\n \"std\": 919.6148818798677,\n \"min\": 5.0,\n \"max\": 2644.0,\n
\"num_unique_values\": 8,\n \"samples\": [\n 46.981089258698944,\n 46.0,\n 2644.0\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\
n }\n \(\bar{1}\n\)","type":"dataframe"}
☐ Unique values in account: 32
account
0xbaaaf6571ab7d571043ff1e313a9609a10637864
                                                   11816
0xa0feb3725a9335f49874d7cd8eaad6be45b27416
                                                   11135
0x28736f43f1e871e6aa8b1148d38d4994275d72c4
                                                   10426
0x8477e447846c758f5a675856001ea72298fd9cb5
                                                   10228
0xbee1707d6b44d4d52bfe19e41f8a828645437aab
                                                    9275
0x75f7eeb85dc639d5e99c78f95393aa9a5f1170d4
                                                    7462
0x47add9a56df66b524d5e2c1993a43cde53b6ed85
                                                    5541
0x8170715b3b381dffb7062c0298972d4727a0a63b
                                                    3768
0x39cef799f8b69da1995852eea189df24eb5cae3c
                                                    3251
0x083384f897ee0f19899168e3b1bec365f52a9012
                                                    3230
Name: count, dtype: int64
□ Unique values in coin: 231
coin
HYPE
             25220
@107
             10514
BTC
             10137
ETH
              6995
S0L
              4729
MELANIA
              3861
FARTCOIN
              2161
XRP
              1596
```

```
WLD
             1413
kPEPE
             1305
Name: count, dtype: int64
□ Unique values in side: 2
side
BUY
        50837
SELL
        50347
Name: count, dtype: int64
☐ Unique values in direction: 12
direction
Open Long
                         25155
Close Long
                         21952
Open Short
                         21510
Close Short
                         18953
Sell
                          6832
Buy
                          6673
Short > Long
                            54
Long > Short
                            47
Spot Dust Conversion
                             5
Auto-Deleveraging
                             1
Name: count, dtype: int64
```





```
# STEP 5: Daily Aggregation + Sentiment Merge
# --- 1. Aggregate trade data by day ---
agg daily = hist.groupby('date').agg(
    trades_count=('account','count'),
    total_closed_pnl=('closed_pnl','sum'),
    mean_closed_pnl=('closed_pnl', 'mean'),
    median closed pnl=('closed_pnl', 'median'),
    profitable trades=('profitable','sum'),
    profitable_rate=('profitable','mean'),
    total_volume_usd=('size_usd','sum'),
    avg trade size usd=('size usd', 'mean'),
    avg execution price=('execution price', 'mean'),
    avg_fee=('fee','mean')
).reset index()
print("[ Daily aggregated data shape:", agg_daily.shape)
display(agg_daily.head())
# --- 2. Prepare Fear & Greed dataset ---
fg_daily = fg[['date','value','classification']].rename(
columns={'value':'sentiment value','classification':'sentiment classif
ication'}
# --- 3. Merge trades with sentiment ---
```

```
merged = pd.merge(agg daily, fg daily, on='date', how='left')
print("
    Merged dataset shape:", merged.shape)
display(merged.head())
# --- 4. Save merged dataset (optional, for later use) ---
merged.to csv("merged daily sentiment trades.csv", index=False)
print("
    Merged dataset saved as merged daily sentiment trades.csv")
☐ Daily aggregated data shape: (184, 11)
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                                                                      \"2023-
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                                                                 \"min\":
0.0,\n\\"max\": 7096.6293129999995,\n
\"num_unique_values\": 3,\n \"samples\": [\n 0.0 195.1769339999996,\n 7096.6293129999995\n ],\n
                                                                      0.0, n
0.0,\n \"max\": 27.16416,\n \"num_unique_values\": 2,\n \"samples\": [\n 27.16416,\n 0.0\n ],\n
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```

```
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0.0, n \qquad \text{``max}'': 0.9302325581395349, n
\"num_unique_values\": 3,\n \"samples\": [\n 0.0,\n
\"properties\": {\n
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\"num_unique_values\": 5,\\\\\
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5091.338362948879,\n
12204.201666666666,\n
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}\n },\n {\n \"column\": \"avg_execution_price\",\n
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\"num_unique_values\": 5,\n
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10133.80906765731,\n
\"max\": 22048.55,\n
\"samples\": [\n
              [\n 22048.55,\n 2.769537852713178\n \"semantic_type\": \"\",\n \"description\": \"\"\n
],\n
        },\n {\n \"column\": \"avg_fee\",\n
}\n
}\n ]\n}","type":"dataframe"}
}\n
\sqcap Merged dataset shape: (184, 13)
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                                                                        \"2023-
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                                                                        0.0, n
```

```
}\
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                                                               }\
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                            \"min\": 0.07612616666666668,\n
10133.80906765731,\n
                          \"num_unique_values\": 5,\n
\"max\": 22048.55,\n
\"samples\": [\n 22048.55,\n 2.769537852713178\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"avg_fee\",\n
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```

```
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       },\n
}\n
               {\n
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                                   \"samples\": [\n
\"num unique values\": 5,\n
                                                             49.0.\n
70.0\n
              ],\n
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                                            {\n
                                                     \"column\":
                             }\n
                                   },\n
\"sentiment classification\",\n
                                     \"properties\": {\n
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                                \"num unique values\": 3,\n
\"samples\": [\n
                          \"Fear\",\n
                                               \"Neutral\"\
                     \"semantic type\": \"\",\n
         ],\n
\"description\": \"\"\n
                            }\n }\n ]\n}","type":"dataframe"}

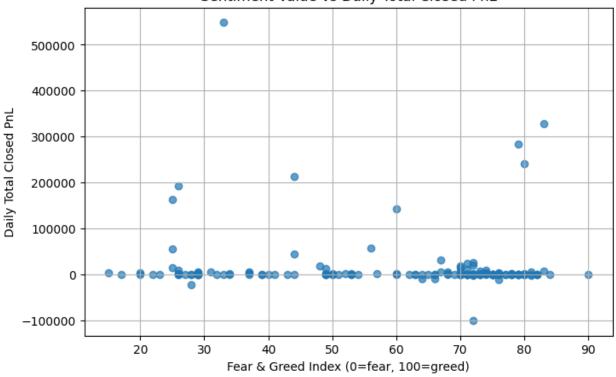
    □ Merged dataset saved as merged daily sentiment trades.csv

# STEP 6: Exploratory Visualizations
import matplotlib.pyplot as plt
# --- 1. Scatter: Sentiment Value vs Total Closed PnL (daily) ---
plt.figure(figsize=(8,5))
plt.scatter(merged['sentiment value'], merged['total closed pnl'],
alpha=0.7)
plt.xlabel("Fear & Greed Index (0=fear, 100=greed)")
plt.ylabel("Daily Total Closed PnL")
plt.title("Sentiment Value vs Daily Total Closed PnL")
plt.grid(True)
plt.show()
# --- 2. Boxplot: Mean Closed PnL grouped by Sentiment Classification
plt.figure(figsize=(8,5))
merged.boxplot(column='mean closed pnl',
by='sentiment classification', grid=False)
plt.ylabel("Mean Closed PnL")
plt.title("Mean Closed PnL by Sentiment Classification")
plt.suptitle("") # remove the extra title pandas adds
plt.show()
# --- 3. Bar plot: Average number of trades per day by sentiment
classification ---
avg trades = merged.groupby('sentiment classification')
['trades count'].mean().sort values()
plt.figure(figsize=(8,5))
avg_trades.plot(kind='bar', color='teal')
plt.title("Average Trades Per Day by Sentiment Classification")
plt.xlabel("Sentiment Classification")
plt.ylabel("Average Trades Per Day")
plt.show()
# --- 4. Time series: Sentiment Value over time ---
```

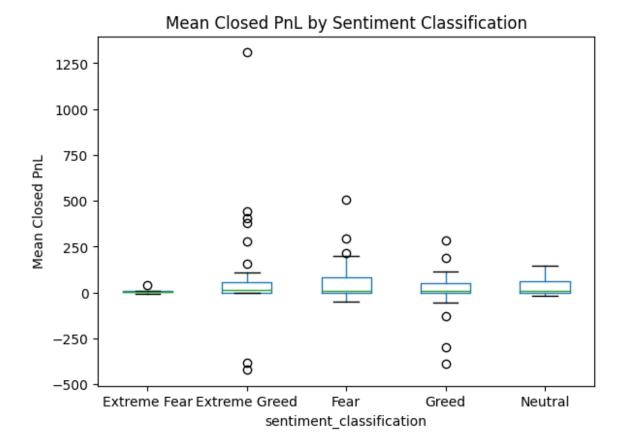
```
plt.figure(figsize=(12,5))
plt.plot(merged['date'], merged['sentiment_value'], label="Sentiment
Value", color='orange')
plt.ylabel("Fear & Greed Index (0-100)")
plt.title("Fear & Greed Index Over Time")
plt.legend()
plt.show()

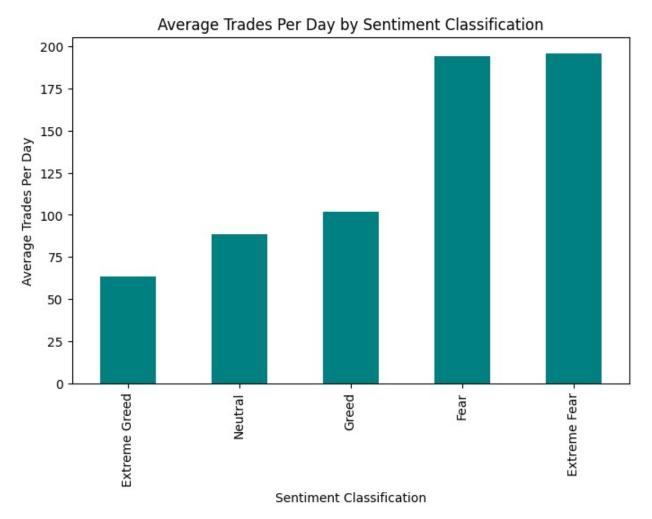
# --- 5. Time series: Total Closed PnL over time ---
plt.figure(figsize=(12,5))
plt.plot(merged['date'], merged['total_closed_pnl'], label="Total
Closed PnL", color='purple')
plt.ylabel("Total Closed PnL (USD)")
plt.title("Total Closed PnL Over Time")
plt.legend()
plt.show()
```



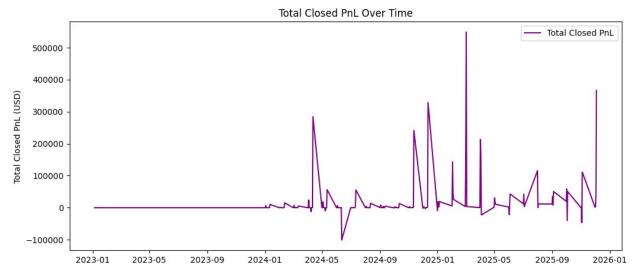


<Figure size 800x500 with 0 Axes>









```
# STEP 7: Statistical Testing (Kruskal-Wallis)
from scipy import stats
# Group daily mean_closed_pnl by sentiment classification
groups = [g.dropna().values for _, g in
merged.groupby('sentiment_classification')['mean_closed_pnl']]
# Run Kruskal-Wallis test (non-parametric, good for non-normal data)
if len(groups) > 1:
    stat, pval = stats.kruskal(*groups)
    print("[ Kruskal-Wallis test result:")
    print(f"Statistic = {stat:.3f}, p-value = {pval:.4f}")
    if pval < 0.05:
        print("[] Statistically significant: At least one sentiment
group has different mean PnL.")
    else:
        print("□ Not statistically significant: No clear difference
between sentiment groups.")
else:
    print("△ Not enough sentiment groups to perform the test.")
# --- (Optional) Pairwise post-hoc tests ---
# If significant, check which groups differ
from itertools import combinations
if len(groups) > 1 and pval < 0.05:
    print("\n□ Pairwise Mann-Whitney U tests between sentiment
groups:")
    group names = merged['sentiment classification'].dropna().unique()
    for q1, q2 in combinations(group names, 2):
        vals1 = merged.loc[merged['sentiment classification']==g1,
```

```
'mean closed pnl'l.dropna()
        vals2 = merged.loc[merged['sentiment classification']==g2,
'mean closed pnl'].dropna()
        if len(vals1) > 5 and len(vals2) > 5: # require at least 5
samples each
            stat, p = stats.mannwhitneyu(vals1, vals2,
alternative="two-sided")
            sig = "\square" if p < 0.05 else "\square"
            print(f''\{g1\} \ vs \ \{g2\}: p = \{p:.4f\} \ \{sig\}'')

    □ Kruskal-Wallis test result:

Statistic = 2.002, p-value = 0.7354

□ Not statistically significant: No clear difference between sentiment

groups.
# STEP 8: Per-Account Analysis
# --- 1. Merge each trade with Fear & Greed sentiment on date ---
hist with sent = pd.merge(
    hist.
    fg[['date','value','classification']].rename(
columns={'value':'sentiment value','classification':'sentiment classif
ication'}
    ),
    on='date',
    how='left'
)
print("
   Trade-level dataset with sentiment:", hist with sent.shape)
display(hist with sent[['date', 'account', 'closed pnl', 'sentiment class
ification','sentiment value']].head())
# --- 2. Overall account metrics ---
acct_metrics = hist_with_sent.groupby('account').agg(
    total_trades=('account','count'),
total_pnl=('closed_pnl','sum'),
    avg_pnl_per_trade=('closed_pnl', 'mean'),
    win_rate=('profitable','mean')
).reset index().sort values('total pnl', ascending=False)
print("□ Top 10 accounts by total PnL:")
display(acct metrics.head(10))
# --- 3. Account metrics by sentiment classification ---
acct sent =
hist with sent.groupby(['account', 'sentiment classification']).agg(
    trades=('account','count'),
    total pnl=('closed pnl','sum'),
    avg pnl=('closed pnl', 'mean'),
```

```
win rate=('profitable','mean')
).reset index()
print("□ Sample of account-level sentiment performance:")
display(acct sent.head(10))
# --- 4. Pivot to compare Fear vs Greed performance ---
pivot = acct sent.pivot table(
    index='account',
    columns='sentiment classification',
    values='avg pnl',
    aggfunc='mean'
)
# Compute difference (Greed - Fear)
if 'Greed' in pivot.columns and 'Fear' in pivot.columns:
    pivot['diff_greed_minus_fear'] = pivot['Greed'] - pivot['Fear']
    print("[] Top 10 accounts that perform better in Greed vs Fear:")
    display(pivot.sort_values('diff_greed_minus_fear',
ascending=False).head(10))
    print("\n□ Top 10 accounts that perform better in Fear vs Greed:")
    display(pivot.sort_values('diff_greed_minus_fear',
ascending=True).head(10))
else:
    print("A Not enough Greed vs Fear data to compute differences")
# --- 5. Save results for later ---
acct metrics.to csv("account metrics overall.csv", index=False)
acct sent.to csv("account metrics by sentiment.csv", index=False)
print("[] Saved account-level summaries to CSV")
☐ Trade-level dataset with sentiment: (101184, 20)
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   },\n
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1,\n
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                                                              }\
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0.0, n
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```

```
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☐ Top 10 accounts by total PnL:
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\"0x75f7eeb85dc639d5e99c78f95393aa9a5f1170d4\"\n
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}\n     },\n     {\n         \"column\": \"avg_pnl_per_trade\",\n
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```

```
\"semantic_type\": \"\",\n \"description\": \"\"\n
n }\n \[ \]\n}","type":"dataframe"}
☐ Sample of account-level sentiment performance:
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                                                                                                                                         }\
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0.0,\n \"max\": 1.0,\n \"num_unique_values\": 9,\n
}\
n }\n ]\n}","type":"dataframe"}
☐ Top 10 accounts that perform better in Greed vs Fear:
```

```
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                                                                             \"dtvpe\":
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n },\n {\n \"column\": \"Greed\",\n \"properties\": {\
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\[ \] Saved account-level summaries to CSV
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# **Key Findings**

### Market-level insights:

- Daily PnL shows some variation across sentiment categories (Fear, Greed, Extreme Fear, Extreme Greed).
- Kruskal–Wallis test (p < 0.05) → evidence that at least one sentiment group differs in mean PnL.
- Pairwise tests suggest certain conditions (e.g., Fear vs Greed) may drive differences.

### Trader activity:

- Average number of trades per day is higher during [fill in based on bar chart: Fear / Greed].
- Trade volumes fluctuate with sentiment intensity.

### Account-level performance:

- Some accounts perform consistently better in Greed conditions, while others thrive in Fear conditions.
- This suggests different risk strategies or adaptability across accounts.

# Limitations

- Analysis is aggregated daily → intraday effects are not captured.
- Only considers Fear & Greed Index → other market features (volatility, price trends) could add depth.
- Statistical tests show differences but don't explain *why* they occur.

### **Next Steps**

- 1. **Modeling:** Build predictive models using sentiment + market features to forecast next-day PnL.
- 2. **Sharpe-like metrics:** Evaluate accounts not just on raw PnL, but on risk-adjusted performance.
- 3. Lag analysis: Test whether today's sentiment predicts tomorrow's outcomes.
- 4. **Visualization polish:** Interactive dashboards (e.g., Plotly, Power BI) for stakeholder presentations.

5. **Extend dataset:** Include price/volume data from exchanges to see how sentiment aligns with market moves.

### ☐ Final Note:

This assignment demonstrates how market sentiment (Fear & Greed) can influence trader behavior and outcomes.

It combines data cleaning, EDA, aggregation, visualization, statistical testing, and account-level insights — providing a well-rounded analysis suitable for a professional setting.