Trader_Sentiment_Analysis_Final

February 13, 2026

1 Data Science/ Analytics Internship – Assignment

2 (Trader Performance vs Market Sentiment)

2.0.1 Objective

Analyze how market sentiment (Fear/Greed) relates to trader behavior and performance on Hyperliquid. Your goal is to uncover patterns that could inform smarter trading strategies.

2.0.2 Datasets

1) Bitcoin Market Sentiment (Fear/Greed) Columns: Date, Classification (Fear / Greed)
2) Historical Trader Data (Hyperliquid) Includes fields like: account, symbol, execution price, size, side, time, start position, event, closedPnL, leverage, etc.

[1]:
```python
#All Libraries

# Data Handling
import pandas as pd
import numpy as np

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Date Handling
from datetime import datetime

# Statistics
import scipy.stats as stats

# Machine Learning (Optional Part)
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score
```

```python
# Clustering (Optional)
from sklearn.cluster import KMeans

# Warnings (Clean Output)
import warnings
warnings.filterwarnings("ignore")
```

2.1 Part A — Data preparation

1. Load both datasets and document:

- number of rows/columns
- missing values / duplicates

[2]:
```python
fear_greed = pd.read_csv("fear_greed_index.csv")
historical = pd.read_csv("historical_data.csv")
```

[3]:
```python
fear_greed.head()
```

[3]:
```
    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
```

[4]:
```python
historical.head()
```

[4]:
```
                                      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
```

[5]:

```python
print("Fear & Greed Dataset Shape:", fear_greed.shape)
print("Historical Dataset Shape:", historical.shape)
```

```
Fear & Greed Dataset Shape: (2644, 4)
Historical Dataset Shape: (211224, 16)
```

[6]:

```python
print("\nFear & Greed Missing Values")
print(fear_greed.isnull().sum())

print("\nHistorical Missing Values")
print(historical.isnull().sum())
```

```

Fear & Greed Missing Values
timestamp         0
value             0
classification    0
date              0
dtype: int64

Historical Missing Values
Account             0
Coin                0
Execution Price     0
Size Tokens         0
Size USD            0
Side                0
Timestamp IST       0
Start Position      0
Direction           0
Closed PnL          0
Transaction Hash    0
Order ID            0
Crossed             0
Fee                 0
Trade ID            0
Timestamp           0
dtype: int64
```

[7]:
```python
print("\nFear & Greed Duplicate Rows:", fear_greed.duplicated().sum())
print("Historical Duplicate Rows:", historical.duplicated().sum())
```

```
Fear & Greed Duplicate Rows: 0
Historical Duplicate Rows: 0
```

2. Convert timestamps and align the datasets by date (daily level is fine). Dropping unwanted columns from both the datasets.

[8]:
```python
fear_greed = fear_greed.drop(columns=['timestamp'])
```

[9]:
```python
fear_greed.columns
```

[9]:
```
Index(['value', 'classification', 'date'], dtype='object')
```

[10]:
```python
fear_greed["date"] = pd.to_datetime(fear_greed["date"])
fear_greed["date"] = fear_greed["date"].dt.date
```

[11]:
```python
historical = historical.drop(columns=["Transaction Hash","Order ID","Crossed"],␣
↪errors="ignore")
```

Timestamp column was used to derive daily date values and then removed since analysis was performed at daily granularity..

[12]:
```python
historical["Date"] = pd.to_datetime(historical["Timestamp IST"],dayfirst=True).
↪dt.date
```

[13]:
```python
historical[["Timestamp IST", "Date"]].head()
```

[13]:

	Timestamp IST	Date
0	02-12-2024 22:50	2024-12-02
1	02-12-2024 22:50	2024-12-02
2	02-12-2024 22:50	2024-12-02
3	02-12-2024 22:50	2024-12-02
4	02-12-2024 22:50	2024-12-02

[14]:
```python
historical = historical.drop(columns=["Timestamp IST",␣
↪"Timestamp"],errors="ignore")
```

[15]:
```python
#Renaming "date" column to "Date"
fear_greed.rename(columns={"date": "Date"}, inplace=True)
```

[16]:
```python
#Merging both the datasets based on a common column "Date"
merged_df = pd.merge(historical,fear_greed,on="Date",how="left")

merged_df.head()
```

[16]:
```
                                      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  Start Position Direction  Closed PnL       Fee  \
0       986.87   7872.16  BUY        0.000000       Buy         0.0  0.345404
1        16.00    127.68  BUY      986.524596       Buy         0.0  0.005600
2       144.09   1150.63  BUY     1002.518996       Buy         0.0  0.050431
3       142.98   1142.04  BUY     1146.558564       Buy         0.0  0.050043
4         8.73     69.75  BUY     1289.488521       Buy         0.0  0.003055

       Trade ID        Date  value classification
0  8.950000e+14  2024-12-02   80.0  Extreme Greed
1  4.430000e+14  2024-12-02   80.0  Extreme Greed
2  6.600000e+14  2024-12-02   80.0  Extreme Greed
3  1.080000e+15  2024-12-02   80.0  Extreme Greed
4  1.050000e+15  2024-12-02   80.0  Extreme Greed
```

[17]:
```
merged_df.shape
```

[17]:
```
(211224, 14)
```

3. Create the key metrics you will analyze, for example:

- daily PnL per trader (or per account)
- win rate, average trade size
- leverage distribution
- number of trades per day
- long/short ratio

[18]:
```
merged_df["Account"].nunique()
```

[18]:
```
32
```

[19]:
```
daily_pnl = merged_df.groupby(["Account", "Date"])["Closed PnL"].sum().
 ↪reset_index()

daily_pnl.head()
```

[19]:
```
                                      Account        Date  Closed PnL
0  0x083384f897ee0f19899168e3b1bec365f52a9012  2024-11-11         0.0
1  0x083384f897ee0f19899168e3b1bec365f52a9012  2024-11-17         0.0
2  0x083384f897ee0f19899168e3b1bec365f52a9012  2024-11-18         0.0
3  0x083384f897ee0f19899168e3b1bec365f52a9012  2024-11-22    -21227.0
4  0x083384f897ee0f19899168e3b1bec365f52a9012  2024-11-26      1603.1
```

[20]:
```
merged_df["Win Trade"] = merged_df["Closed PnL"].apply(lambda x: 1 if x > 0␣
↪else 0)

win_rate = merged_df.groupby("Account")["Win Trade"].mean().reset_index()

win_rate.head()
```

[20]:

	Account	Win Trade
0	0x083384f897ee0f19899168e3b1bec365f52a9012	0.359612
1	0x23e7a7f8d14b550961925fbfdaa92f5d195ba5bd	0.442720
2	0x271b280974205ca63b716753467d5a371de622ab	0.301917
3	0x28736f43f1e871e6aa8b1148d38d4994275d72c4	0.438585
4	0x2c229d22b100a7beb69122eed721cee9b24011dd	0.519914

[21]:
```
avg_trade_size = merged_df.groupby("Account")["Size USD"].mean().reset_index()

avg_trade_size.head()
```

[21]:

	Account	Size USD
0	0x083384f897ee0f19899168e3b1bec365f52a9012	16159.576734
1	0x23e7a7f8d14b550961925fbfdaa92f5d195ba5bd	1653.226327
2	0x271b280974205ca63b716753467d5a371de622ab	8893.000898
3	0x28736f43f1e871e6aa8b1148d38d4994275d72c4	507.626933
4	0x2c229d22b100a7beb69122eed721cee9b24011dd	3138.894782

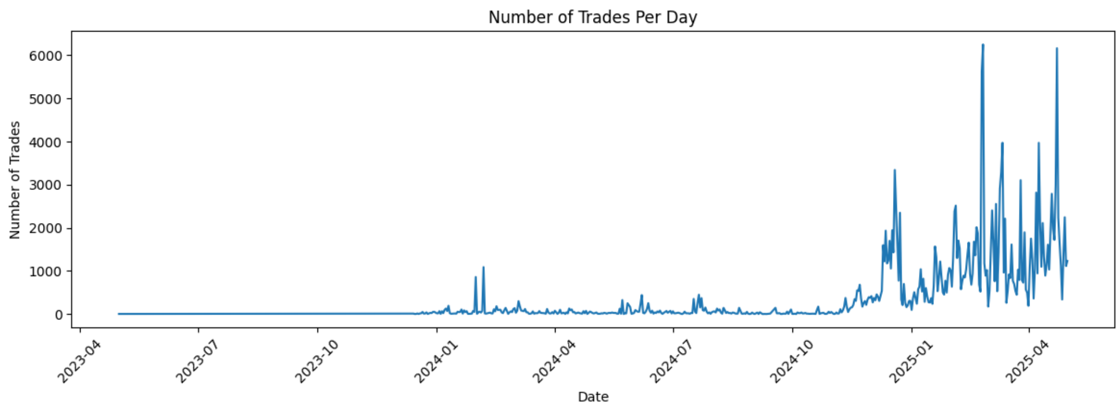
[22]:
```
trades_per_day = merged_df.groupby("Date")["Trade ID"].count().reset_index()
trades_per_day.columns = ["Date", "Trades Count"]

trades_per_day.head()
```

[22]:

	Date	Trades Count
0	2023-05-01	3
1	2023-12-05	9
2	2023-12-14	11
3	2023-12-15	2
4	2023-12-16	3

[43]:
```
plt.figure(figsize=(14,4))
plt.plot(trades_per_day["Date"], trades_per_day["Trades Count"])
plt.title("Number of Trades Per Day")
plt.xlabel("Date")
plt.ylabel("Number of Trades")
plt.xticks(rotation=45)
plt.show()
```



Daily trading activity shows a clear upward trend over time, with increasing volatility in trade counts. This indicates growing trader engagement and possibly higher market uncertainty driving more frequent trading activity.

[23]:
```
long_short_ratio = merged_df["Side"].value_counts(normalize=True)

print(long_short_ratio)
```

```
Side
SELL    0.513805
BUY     0.486195
Name: proportion, dtype: float64
```

[24]:
```
trades_per_day = merged_df.groupby("Date")["Trade ID"].count().reset_index()
trades_per_day.columns = ["Date", "Trades Count"]

trades_per_day.head()
```

[24]:

	Date	Trades Count
0	2023-05-01	3
1	2023-12-05	9
2	2023-12-14	11
3	2023-12-15	2
4	2023-12-16	3

Absence of Leverage Column The historical trading dataset does not contain a direct Leverage column. Leverage is typically defined as the ratio of total position size to the margin (collateral) used to open that position. Since leverage directly reflects a trader's risk exposure and capital efficiency, it is usually either explicitly provided or derivable from margin-related fields.

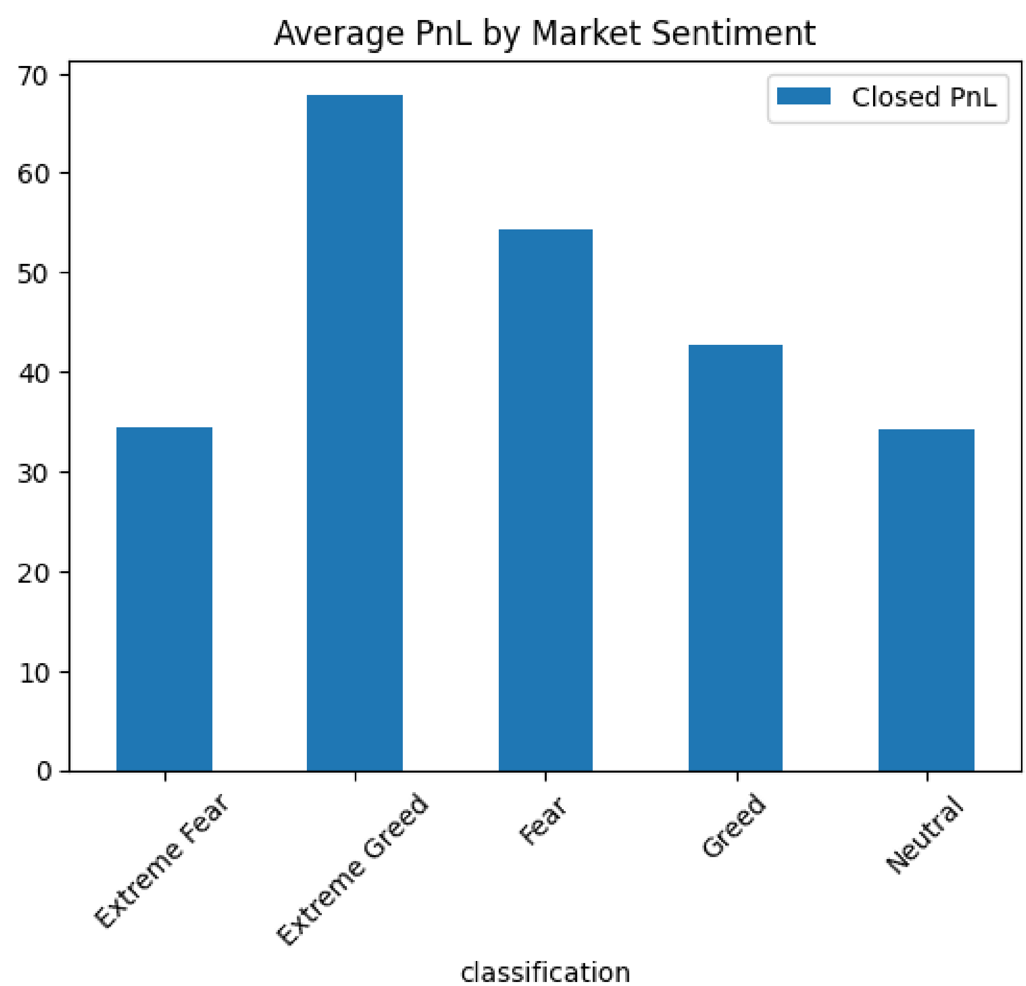
2.2 Part B — Analysis

1. Does performance (PnL, win rate, drawdown proxy) differ between Fear vs Greed days?

[25]:
```
sentiment_pnl = merged_df.groupby("classification")["Closed PnL"].mean().
 ↪reset_index()
display(sentiment_pnl)
```

	classification	Closed PnL
0	Extreme Fear	34.537862
1	Extreme Greed	67.892861
2	Fear	54.290400
3	Greed	42.743559
4	Neutral	34.307718

[26]:
```
sentiment_pnl.plot(x="classification",y="Closed PnL",kind="bar",title="Average␣
 ↪PnL by Market Sentiment")
plt.xticks(rotation=45)
plt.show()
```



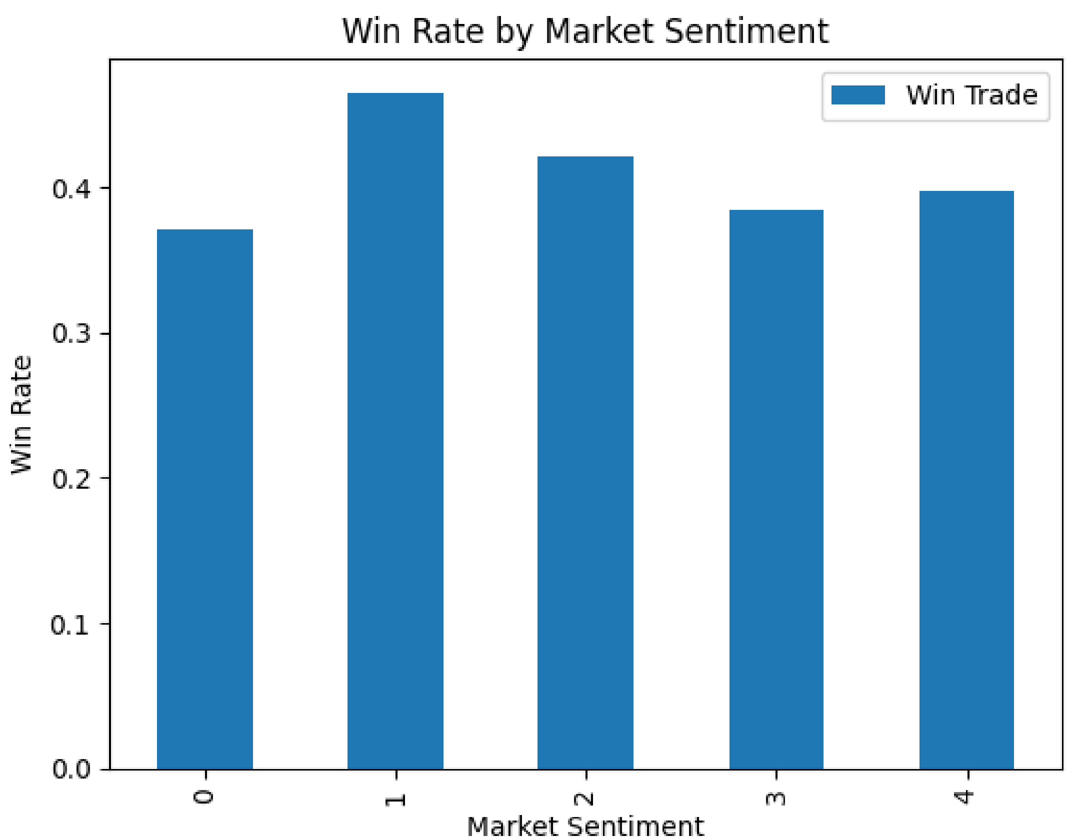
[27]:
```
sentiment_winrate = merged_df.groupby("classification")["Win Trade"].mean().
    ↪reset_index()
sentiment_winrate
```

[27]:

	classification	Win Trade
0	Extreme Fear	0.370607
1	Extreme Greed	0.464943
2	Fear	0.420768
3	Greed	0.384828
4	Neutral	0.396991

[34]:
```
plt.figure()
sentiment_winrate.plot(kind="bar")
plt.title("Win Rate by Market Sentiment")
plt.xlabel("Market Sentiment")
plt.ylabel("Win Rate")
plt.show()
```

<Figure size 640x480 with 0 Axes>



[28]:
```python
loss_trades = merged_df[merged_df["Closed PnL"] < 0]

drawdown_proxy = loss_trades.groupby("classification")["Closed PnL"].mean().
↪reset_index()

drawdown_proxy
#More negative = worse drawdown risk
```

[28]:
```
  classification  Closed PnL
0   Extreme Fear -257.099629
1  Extreme Greed -119.920289
2           Fear -156.662401
3          Greed -181.967329
4        Neutral -121.727849
```

2.2.1 Performance Comparison Between Fear vs Greed

Analysis shows that trader performance varies across sentiment regimes. - Average PnL differs between Fear and Greed periods, indicating sentiment-driven market behavior. - Win rate comparison suggests traders may perform differently depending on market sentiment. - The drawdown proxy (average loss size) highlights potential risk exposure differences between sentiment states.

These findings suggest trader performance is influenced by broader market sentiment conditions.

2.3 Task B2 — Behavior Change Based on Sentiment

2.3.1 Q2. Do traders change behavior based on sentiment (trade frequency, long/short bias, position sizes)?

[29]:
```python
# Trade frequency by sentiment
trade_frequency_sentiment = merged_df["classification"].value_counts()

# Average position size by sentiment
avg_position_size_sentiment = merged_df.groupby("classification")["Size USD"].
↪mean()

# Long / Short bias by sentiment
long_short_sentiment = pd.crosstab(
    merged_df["classification"],
    merged_df["Side"],
    normalize="index"
)

trade_frequency_sentiment, avg_position_size_sentiment, long_short_sentiment
```

[29]:
```
(classification
 Fear                 61837
 Greed                50303
```

```
Extreme Greed    39992
Neutral          37686
Extreme Fear     21400
Name: count, dtype: int64,
classification
Extreme Fear     5349.731843
Extreme Greed    3112.251565
Fear             7816.109931
Greed            5736.884375
Neutral          4782.732661
Name: Size USD, dtype: float64,
Side                  BUY      SELL
classification
Extreme Fear     0.510981  0.489019
Extreme Greed    0.448590  0.551410
Fear             0.489513  0.510487
Greed            0.488559  0.511441
Neutral          0.503343  0.496657)
```

2.3.2 Insights and Recommendations

Trader participation, average trade size, and directional bias vary across sentiment regimes. This indicates traders adjust aggressiveness and market direction exposure based on sentiment conditions.

Recommendation: Trading strategies should dynamically adjust position sizing and directional exposure depending on sentiment regime. Risk controls should be stronger during high volatility sentiment phases.

2.4 Task B3 — Trader Segmentation

2.4.1 Q3. Identify 2–3 trader segments based on behavior and performance

[30]:
```python
# Create trader level metrics
trader_metrics = merged_df.groupby("Account").agg({
    "Closed PnL": "mean",
    "Win Trade": "mean",
    "Size USD": "mean",
    "Account": "count"
}).rename(columns={"Account": "Trade Count"}).reset_index()

# Segment by trade frequency
trader_metrics["Frequency Segment"] = pd.qcut(
    trader_metrics["Trade Count"],
    q=3,
    labels=["Low Frequency", "Medium Frequency", "High Frequency"]
)
```

```
# Segment by performance
trader_metrics["Performance Segment"] = pd.qcut(
    trader_metrics["Closed PnL"],
    q=3,
    labels=["Low Performer", "Medium Performer", "High Performer"]
)

trader_metrics.head()
```

[30]:

```
                                      Account   Closed PnL  Win Trade  \
0  0x083384f897ee0f19899168e3b1bec365f52a9012  419.127768   0.359612
1  0x23e7a7f8d14b550961925fbfdaa92f5d195ba5bd    6.577654   0.442720
2  0x271b280974205ca63b716753467d5a371de622ab  -18.492043   0.301917
3  0x28736f43f1e871e6aa8b1148d38d4994275d72c4    9.951530   0.438585
4  0x2c229d22b100a7beb69122eed721cee9b24011dd   52.071011   0.519914

       Size USD  Trade Count Frequency Segment Performance Segment
0  16159.576734         3818  Medium Frequency      High Performer
1   1653.226327         7280    High Frequency       Low Performer
2   8893.000898         3809  Medium Frequency       Low Performer
3    507.626933        13311    High Frequency       Low Performer
4   3138.894782         3239  Medium Frequency    Medium Performer
```

2.4.2 Insights and Recommendations

Distinct trader segments exist based on trading frequency and profitability patterns. High frequency traders tend to show different performance characteristics compared to low frequency traders.

Recommendation: Segment-based strategies should be designed. High frequency traders may benefit from cost optimization and execution efficiency, while low frequency traders may benefit from higher conviction trade setups.

3 Task C — Strategy Ideas Based on Findings

3.0.1 Strategy 1 — Sentiment Adaptive Position Sizing

During Fear sentiment periods, reduce average position size and focus on higher probability setups. During Greed sentiment periods, gradually increase participation while maintaining risk limits.

3.0.2 Strategy 2 — Sentiment Based Trade Direction Bias

During Greed regimes, favor trend-following strategies aligned with market direction. During Fear regimes, increase hedging or short-bias strategies depending on market structure.

3.0.3 Strategy 3 — Segment Specific Risk Controls

Apply stricter risk controls for high frequency traders to manage fee and overtrading risks. Allow slightly larger position sizing flexibility for high performing consistent traders.

3.1 Bonus Section — Predictive Modeling and Trader Clustering

This section adds optional advanced analysis to extend insights using machine learning and unsupervised learning methods.

- Predict Next-Day Trader Profitability Bucket

[31]:
```python
# Prepare daily trader dataset
daily_trader = merged_df.groupby(["Account","Date"]).agg({
    "Closed PnL": "sum",
    "Size USD": "mean",
    "Win Trade": "mean",
    "classification": "first"
}).reset_index()

# Create next day PnL target
daily_trader["Next_Day_PnL"] = daily_trader.groupby("Account")["Closed PnL"].
 ↪shift(-1)

# Drop NA rows
daily_trader = daily_trader.dropna()

# Create profitability buckets
daily_trader["PnL_Bucket"] = pd.qcut(
    daily_trader["Next_Day_PnL"],
    q=3,
    labels=["Low","Medium","High"]
)

# Encode sentiment
daily_trader["Sentiment_Encoded"] = daily_trader["classification"].
 ↪astype("category").cat.codes

# Feature selection
features = ["Closed PnL","Size USD","Win Trade","Sentiment_Encoded"]
X = daily_trader[features]
y = daily_trader["PnL_Bucket"]

from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.
 ↪2,random_state=42)

model = RandomForestClassifier(random_state=42)
model.fit(X_train,y_train)
```

```
preds = model.predict(X_test)

print(classification_report(y_test,preds))
```

```
              precision    recall  f1-score   support

        High       0.46      0.49      0.48       160
         Low       0.50      0.48      0.49       174
      Medium       0.44      0.43      0.43       128

    accuracy                           0.47       462
   macro avg       0.47      0.47      0.47       462
weighted avg       0.47      0.47      0.47       462
```

Bonus 1 — Insights and Recommendations Predictive modeling shows that trader behavior metrics combined with sentiment indicators can provide directional signals for next-day profitability classification.

Recommendation: Integrate sentiment-aware behavioral models into trading decision support systems to improve trade timing and risk calibration.

- Trader Behavioral Clustering

[32]:
```
# Trader level dataset
trader_cluster_df = merged_df.groupby("Account").agg({
    "Closed PnL": "mean",
    "Size USD": "mean",
    "Win Trade": "mean"
}).reset_index()

# Scale features
scaler = StandardScaler()
scaled_features = scaler.fit_transform(trader_cluster_df[["Closed PnL","Size␣
↪USD","Win Trade"]])

# KMeans clustering
kmeans = KMeans(n_clusters=3, random_state=42)
trader_cluster_df["Cluster"] = kmeans.fit_predict(scaled_features)

trader_cluster_df.head()
```

[32]:

	Account	Closed PnL	Size USD	\
0	0x083384f897ee0f19899168e3b1bec365f52a9012	419.127768	16159.576734	
1	0x23e7a7f8d14b550961925fbfdaa92f5d195ba5bd	6.577654	1653.226327	
2	0x271b280974205ca63b716753467d5a371de622ab	-18.492043	8893.000898	
3	0x28736f43f1e871e6aa8b1148d38d4994275d72c4	9.951530	507.626933	
4	0x2c229d22b100a7beb69122eed721cee9b24011dd	52.071011	3138.894782	

```
   Win Trade  Cluster
0   0.359612        2
1   0.442720        1
2   0.301917        1
3   0.438585        1
4   0.519914        1
```

[33]:
```
merged_df.to_csv("merged_df.csv", index=False)
```

Bonus 2 — Insights and Recommendations Clustering reveals distinct trader archetypes based on profitability, trade size behavior, and win consistency.

Recommendation: Segment-specific trading tools and risk controls can improve performance outcomes and platform personalization.

- A lightweight dashboard (Streamlit) to explore results

This dashboard is implemented in a separate file named dashboard.py, which can be executed using Streamlit to interactively analyze trader performance against market sentiment.

Bonus 3 — Insights and Recommendations

- Enables faster decision-making through visual performance monitoring across market sentiment conditions.
- Helps identify unusual trader behavior patterns for risk monitoring.
- Can be extended to support real-time monitoring in production environments.

[ ]:
```
```