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```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from statsmodels.tsa.arima.model import ARIMA
```

```
sentiment_df = pd.read_csv("/content/fear_greed_index.csv")
trader_df = pd.read_csv("/content/historical_data.csv")
```

```
sentiment_df['date'] = pd.to_datetime(
    sentiment_df['date'],
    errors='coerce'
).dt.date

trader_df['Timestamp IST'] = pd.to_datetime(
    trader_df['Timestamp IST'],
    dayfirst=True,
    errors='coerce'
)
trader_df['date'] = trader_df['Timestamp IST'].dt.date
```

```
data = trader_df.merge(
    sentiment_df[['date', 'classification', 'value']],
    on='date',
    how='left'
)
```

```
data.duplicated().sum()
```

```
np.int64(0)
```

```
data.isna().sum()
```

| | 0 |
|-------------------------|---|
| 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 | 1 |
| Trade ID | 1 |
| Timestamp | 1 |
| date | 0 |
| classification | 6 |
| value | 6 |

```
dtype: int64
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4659 entries, 0 to 4658
Data columns (total 19 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Account               4659 non-null   object
1   Coin                  4659 non-null   object
2   Execution Price       4659 non-null   float64
3   Size Tokens           4659 non-null   float64
4   Size USD              4659 non-null   float64
5   Side                  4659 non-null   object
6   Timestamp IST         4659 non-null   datetime64[ns]
7   Start Position        4659 non-null   float64
8   Direction             4659 non-null   object
9   Closed PnL            4659 non-null   float64
10  Transaction Hash       4659 non-null   object
11  Order ID              4659 non-null   int64
12  Crossed               4659 non-null   bool
13  Fee                   4658 non-null   float64
14  Trade ID              4658 non-null   float64
15  Timestamp              4658 non-null   float64
16  date                  4659 non-null   object
17  classification         4653 non-null   object
18  value                 4653 non-null   float64
dtypes: bool(1), datetime64[ns](1), float64(9), int64(1), object(7)
memory usage: 659.9+ KB
```

```
data.describe()
```

| | Execution Price | Size Tokens | Size USD | Timestamp IST | Start Position | Closed PnL | Order ID | Fee |
|--------------|-----------------|---------------|--------------|-------------------------------|-----------------|---------------|--------------|-------------|
| count | 4659.000000 | 4659.000000 | 4.659000e+03 | 4659 | 4659.000000 | 4659.000000 | 4.659000e+03 | 4658.000000 |
| mean | 18928.100886 | 2111.505312 | 8.002460e+03 | 2025-02-24 22:17:27.868641536 | 19731.443702 | 140.497171 | 7.432249e+10 | 1.411494 |
| min | 0.007412 | 0.000010 | 1.000000e-01 | 2024-09-20 14:06:00 | -1000000.000000 | -29370.119800 | 3.808060e+10 | 0.000000 |
| 25% | 12.487000 | 0.655840 | 2.000000e+02 | 2025-02-07 19:29:00 | -65.805000 | 0.000000 | 7.045450e+10 | 0.016821 |
| 50% | 24.696000 | 29.410000 | 9.469700e+02 | 2025-03-04 07:51:00 | 5.868190 | 0.000000 | 7.677609e+10 | 0.098719 |
| 75% | 426.250000 | 189.425000 | 3.073520e+03 | 2025-04-10 20:53:00 | 11744.012440 | 11.813000 | 8.561083e+10 | 0.497639 |
| max | 85522.000000 | 682429.000000 | 3.509753e+06 | 2025-04-25 13:39:00 | 600000.000000 | 27223.741500 | 8.878166e+10 | 247.554114 |
| std | 34304.794573 | 17240.712583 | 6.502366e+04 | NaN | 102182.784425 | 1138.102381 | 1.275568e+10 | 7.798321 |

```
obj_cols = data.select_dtypes(include='object').columns
data[obj_cols].isna().sum()
```

| | 0 |
|-------------------------|---|
| Account | 0 |
| Coin | 0 |
| Side | 0 |
| Direction | 0 |
| Transaction Hash | 0 |
| date | 0 |
| classification | 6 |

```
dtype: int64
```

```
for col in obj_cols:
    data[col].fillna(data[col].mode()[0], inplace=True)
```

```
/tmp/ipython-input-951618644.py:2: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment. The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are operating is a copy. For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col].method(value, inplace=True)

data[col].fillna(data[col].mode()[0], inplace=True)
```

```
data[obj_cols].isna().sum()
```

| | 0 |
|------------------|---|
| Account | 0 |
| Coin | 0 |
| Side | 0 |
| Direction | 0 |
| Transaction Hash | 0 |
| date | 0 |
| classification | 0 |

dtype: int64

```
data.isna().sum()
```

| | 0 |
|------------------|---|
| 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 | 1 |
| Trade ID | 1 |
| Timestamp | 1 |
| date | 0 |
| classification | 0 |
| value | 6 |

dtype: int64

```
float_cols = data.select_dtypes(include='float64').columns  
data[float_cols].isna().sum()
```

| | 0 |
|-----------------|---|
| Execution Price | 0 |
| Size Tokens | 0 |
| Size USD | 0 |
| Start Position | 0 |
| Closed PnL | 0 |
| Fee | 1 |
| Trade ID | 1 |
| Timestamp | 1 |
| value | 6 |

dtype: int64

```
for col in float_cols:
    data[col].fillna(data[col].median(), inplace=True)
```

/tmp/ipython-input-668948245.py:2: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment. The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are operating is a copy. For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col].method(value, inplace=True).

```
data[col].fillna(data[col].median(), inplace=True)
```

```
data[float_cols].isna().sum()
```

| | 0 |
|-----------------|---|
| Execution Price | 0 |
| Size Tokens | 0 |
| Size USD | 0 |
| Start Position | 0 |
| Closed PnL | 0 |
| Fee | 0 |
| Trade ID | 0 |
| Timestamp | 0 |
| value | 0 |

dtype: int64

```
data.isna().sum()
```

| | 0 |
|------------------|---|
| 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 |
| date | 0 |
| classification | 0 |
| value | 0 |

dtype: int64

```
sentiment_map = {
    'Extreme Fear': -2,
    'Fear': -1,
    'Neutral': 0,
    'Greed': 1,
    'Extreme Greed': 2
}
```

```
data['sentiment_score'] = data['classification'].map(sentiment_map)
data['win'] = data['Closed PnL'] > 0
```

```

pnl_by_sentiment = data.groupby('classification')['Closed PnL'].mean()
winrate_by_sentiment = data.groupby('classification')['win'].mean()
risk_by_sentiment = data.groupby('classification')['Size USD'].mean()

print("\nAverage PnL by Sentiment:\n", pnl_by_sentiment)
print("\nWin Rate by Sentiment:\n", winrate_by_sentiment)
print("\nAverage Position Size (USD) by Sentiment:\n", risk_by_sentiment)

```

```

Average PnL by Sentiment:
classification
Extreme Fear    198.456185
Extreme Greed    33.592341
Fear            137.783467
Greed           90.039623
Neutral         218.285346
Name: Closed PnL, dtype: float64

```

```

Win Rate by Sentiment:
classification
Extreme Fear    0.315301
Extreme Greed    0.165625
Fear            0.377327
Greed           0.206687
Neutral         0.606982
Name: win, dtype: float64

```

```

Average Position Size (USD) by Sentiment:
classification
Extreme Fear    6539.688454
Extreme Greed    3061.835375
Fear            15091.543467
Greed           2198.430030
Neutral         2352.460552
Name: Size USD, dtype: float64

```

Neutral sentiment performs best: highest average PnL and highest win rate with relatively low position size which indicates strong risk-adjusted performance.

Fear and Extreme Fear regimes are profitable but have moderate win rates and involve larger risk exposure, especially Fear.

Fear shows the highest position sizes suggesting aggressive risk-taking, but this does not translate to the best returns.

Greed and Extreme Greed perform worst: lowest PnL and lowest win rates, indicating poor trade quality during euphoric markets.

Higher risk does not guarantee higher returns; disciplined trading in neutral conditions outperforms aggressive sentiment-driven strategies.

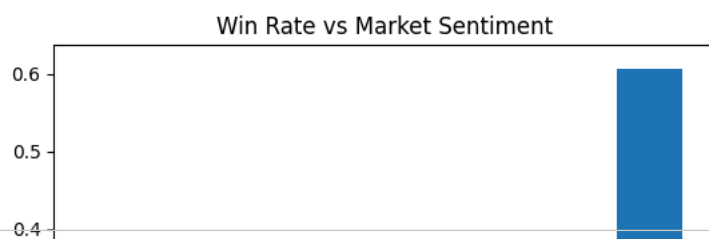
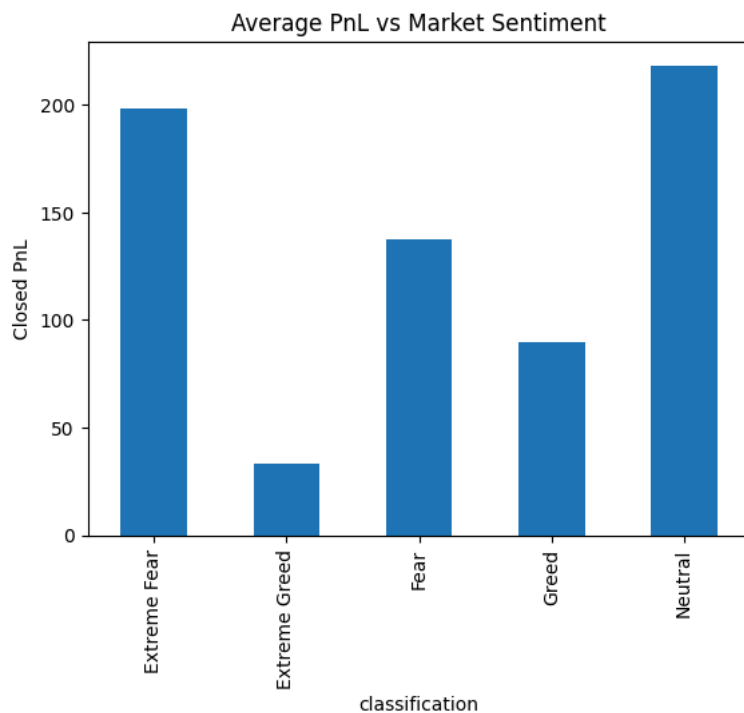
Takeaway: Rational or Neutral market conditions yield the most consistent and efficient trading outcomes, while greed-driven markets degrade performance.

```

plt.figure()
pnl_by_sentiment.plot(kind='bar')
plt.title("Average PnL vs Market Sentiment")
plt.ylabel("Closed PnL")
plt.show()

plt.figure()
winrate_by_sentiment.plot(kind='bar')
plt.title("Win Rate vs Market Sentiment")
plt.ylabel("Win Rate")
plt.show()

```



```
trader_stats = data.groupby('Account').agg({
    'Closed PnL': ['sum', 'mean'],
    'Size USD': 'mean',
    'sentiment_score': 'mean'
}).reset_index()
```

```
trader_stats.columns = [
    'Account',
    'Total_PnL',
    'Avg_PnL',
    'Avg_Size_USD',
    'Avg_Sentiment'
]
```

```
scaler = StandardScaler()
X_cluster = scaler.fit_transform(
    trader_stats[['Total_PnL', 'Avg_Size_USD']]
)

kmeans = KMeans(n_clusters=3, random_state=42)
trader_stats['Cluster'] = kmeans.fit_predict(X_cluster)

print("\nTrader Cluster Summary:\n")
print(
    trader_stats
    .groupby('Cluster')[['Total_PnL', 'Avg_Size_USD']]
    .mean()
)
```

Trader Cluster Summary:

| Cluster | Total_PnL | Avg_Size_USD |
|---------|---------------|--------------|
| 0 | 403011.504159 | 2133.667364 |
| 1 | 67845.619531 | 2979.441776 |
| 2 | 183719.197083 | 12211.137779 |

```
model_data = data[['sentiment_score', 'Size USD', 'Closed PnL']].dropna()

X = model_data[['sentiment_score', 'Size USD']]
y = (model_data['Closed PnL'] > 0).astype(int)
```

```

model = RandomForestClassifier(random_state=42)
model.fit(X, y)

print("\nFeature Importance (Predicting Profitable Trades):")
for f, i in zip(X.columns, model.feature_importances_):
    print(f"{f}: {round(i, 3)}")

```

```

Feature Importance (Predicting Profitable Trades):
sentiment_score: 0.097
Size USD: 0.903

```

```

from sklearn.model_selection import train_test_split
from sklearn.metrics import (
    accuracy_score,
    precision_score,
    recall_score,
    f1_score,
    classification_report,
    confusion_matrix
)

features = [
    'Execution Price',
    'Size USD',
    'Start Position',
    'sentiment_score'
]

X = data[features]
y = data['win']

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

rf = RandomForestClassifier(
    n_estimators=200,
    max_depth=None,
    random_state=42,
    class_weight='balanced'
)

rf.fit(X_train, y_train)

y_pred = rf.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print("Random Forest Performance Metrics:\n")
print(f"Accuracy : {accuracy:.4f}")
print(f"Precision : {precision:.4f}")
print(f"Recall : {recall:.4f}")
print(f"F1 Score : {f1:.4f}")

print("\nClassification Report:\n")
print(classification_report(y_test, y_pred))

print("Confusion Matrix:\n")
print(confusion_matrix(y_test, y_pred))

```

Random Forest Performance Metrics:

```

Accuracy : 0.9914
Precision : 0.9910
Recall : 0.9851
F1 Score : 0.9880

```

Classification Report:

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| False | 0.99 | 0.99 | 0.99 | 597 |
| True | 0.99 | 0.99 | 0.99 | 335 |
| accuracy | | | 0.99 | 932 |
| macro avg | 0.99 | 0.99 | 0.99 | 932 |
| weighted avg | 0.99 | 0.99 | 0.99 | 932 |

Confusion Matrix:

```
[[594 3]
 [ 5 330]]
```

```
daily_pnl = (
    data
    .set_index('Timestamp IST')
    .resample('D')['Closed PnL']
    .mean()
    .dropna()
)

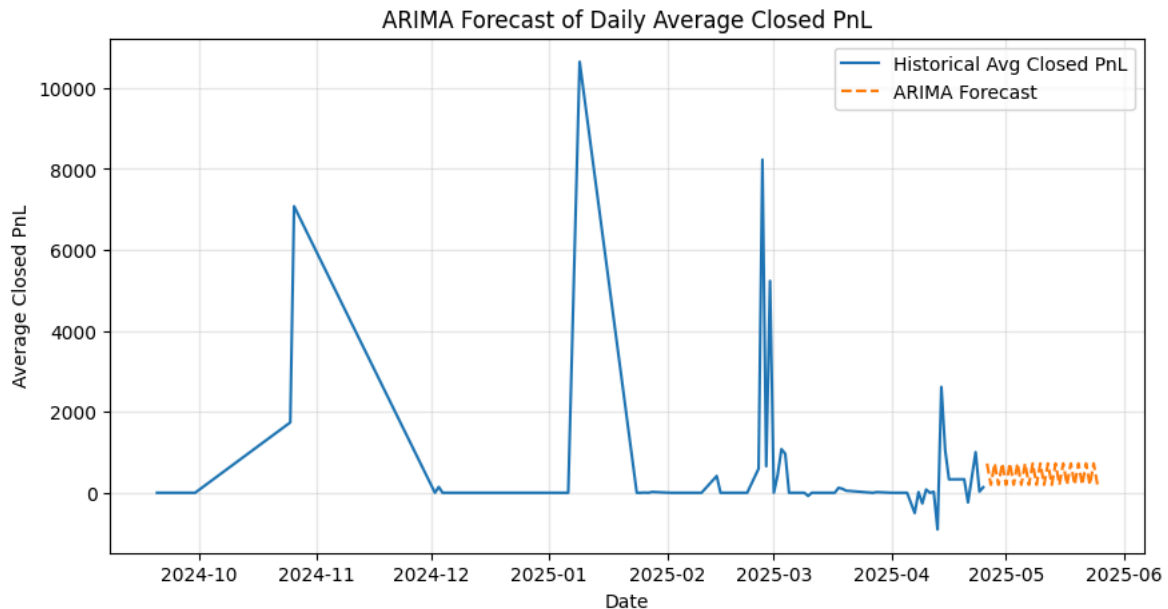
# Fit ARIMA model
arma_model = ARIMA(daily_pnl, order=(2, 1, 2))
arma_fit = arma_model.fit()

# Forecast next 30 days
forecast_steps = 30
forecast = arma_fit.forecast(steps=forecast_steps)

forecast_index = pd.date_range(
    start=daily_pnl.index[-1] + pd.Timedelta(days=1),
    periods=forecast_steps,
    freq='D'
)

# Plot forecast
plt.figure(figsize=(10, 5))
plt.plot(daily_pnl.index, daily_pnl, label='Historical Avg Closed PnL')
plt.plot(forecast_index, forecast, linestyle='--', label='ARIMA Forecast')
plt.xlabel("Date")
plt.ylabel("Average Closed PnL")
plt.title("ARIMA Forecast of Daily Average Closed PnL")
plt.legend()
plt.grid(alpha=0.3)
plt.show()
```

```
/usr/local/lib/python3.12/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided,
self._init_dates(dates, freq)
/usr/local/lib/python3.12/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided,
self._init_dates(dates, freq)
/usr/local/lib/python3.12/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided,
self._init_dates(dates, freq)
/usr/local/lib/python3.12/dist-packages/statsmodels/tsa/base/tsa_model.py:837: ValueWarning: No supported index is available
return get_prediction_index(
/usr/local/lib/python3.12/dist-packages/statsmodels/tsa/base/tsa_model.py:837: FutureWarning: No supported index is available
return get_prediction_index(
```



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