```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

plt.style.use("default")
```

```
trades = pd.read_csv("/content/historical_data.csv")
sentiment = pd.read_csv("/content/fear_greed_index.csv")

print(trades.shape)
print(sentiment.shape)

trades.head()
```

```
(211224, 16)
(2644, 4)
```

	Account	Coin	Execution Price	Size Tokens	Size USD	Side	Timestamp IST	Start Position	Direction	Closed PnL
0	0xae5eacaf9c6b9111fd53034a602c192a04e082ed	@107	7.9769	986.87	7872.16	BUY	02-12-2024 22:50	0.000000	Buy	0.0
1	0xae5eacaf9c6b9111fd53034a602c192a04e082ed	@107	7.9800	16.00	127.68	BUY	02-12-2024 22:50	986.524596	Buy	0.0
2	0xae5eacaf9c6b9111fd53034a602c192a04e082ed	@107	7.9855	144.09	1150.63	BUY	02-12-2024 22:50	1002.518996	Buy	0.0
3	0xae5eacaf9c6b9111fd53034a602c192a04e082ed	@107	7.9874	142.98	1142.04	BUY	02-12-2024 22:50	1146.558564	Buy	0.0
4	0xae5eacaf9c6b9111fd53034a602c192a04e082ed	@107	7.9894	8.73	69.75	BUY	02-12-2024 22:50	1289.488521	Buy	0.0

```
print(trades.columns)
print(sentiment.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')
Index(['timestamp', 'value', 'classification', 'date'], dtype='object')
```

```
trades['Timestamp'] = pd.to_datetime(trades['Timestamp'], unit='ms')
trades['date'] = trades['Timestamp'].dt.date
```

```
sentiment['timestamp'] = pd.to_datetime(sentiment['timestamp'], unit='ms')
sentiment['date'] = sentiment['timestamp'].dt.date
```

```
# converting numeric timestamp
sentiment['timestamp'] = pd.to_numeric(sentiment['timestamp'], errors='coerce')
# detecting scale and normalize to seconds
sentiment.loc[sentiment['timestamp'] > 1e12, 'timestamp'] /= 1000   # ms → sec
sentiment.loc[sentiment['timestamp'] > 1e10, 'timestamp'] /= 1000   # µs → sec
# converting to datetime
sentiment['timestamp'] = pd.to_datetime(sentiment['timestamp'], unit='s')
sentiment['date'] = sentiment['timestamp'].dt.date
```

```
sentiment['classification'] = sentiment['classification'].str.strip().str.capitalize()

sentiment['sentiment_flag'] = sentiment['classification'].map({
    'Fear': 0,
    'Greed': 1
})
```

```
sentiment = sentiment.dropna(subset=['sentiment_flag'])
```

```
print(sentiment[['timestamp','date','classification','sentiment_flag']].head())
print(sentiment['date'].nunique(), "unique sentiment days")
```

```
            timestamp        date classification  sentiment_flag
0 2018-02-01 05:30:00  2018-02-01           Fear             0.0
2 2018-02-03 05:30:00  2018-02-03           Fear             0.0
6 2018-02-07 05:30:00  2018-02-07           Fear             0.0
7 2018-02-08 05:30:00  2018-02-08           Fear             0.0
8 2018-02-09 05:30:00  2018-02-09           Fear             0.0
1414 unique sentiment days
```

```
# converting trades timestamp
trades['Timestamp'] = pd.to_datetime(trades['Timestamp'])
trades['date'] = trades['Timestamp'].dt.date

print(trades[['Timestamp', 'date', 'Closed PnL']].head())
print("Trade days:", trades['date'].nunique())
```

```
            Timestamp        date  Closed PnL
0 2024-10-27 03:33:20  2024-10-27         0.0
1 2024-10-27 03:33:20  2024-10-27         0.0
2 2024-10-27 03:33:20  2024-10-27         0.0
3 2024-10-27 03:33:20  2024-10-27         0.0
4 2024-10-27 03:33:20  2024-10-27         0.0
Trade days: 7
```

```
merged = trades.merge(
    sentiment[['date', 'sentiment_flag']],
    on='date',
    how='left'
)

print(merged[['date', 'Closed PnL', 'sentiment_flag']].head())
print("Missing sentiment rows:", merged['sentiment_flag'].isna().sum())
```

```
         date  Closed PnL  sentiment_flag
0  2024-10-27         0.0             1.0
1  2024-10-27         0.0             1.0
2  2024-10-27         0.0             1.0
3  2024-10-27         0.0             1.0
4  2024-10-27         0.0             1.0
Missing sentiment rows: 41064
```

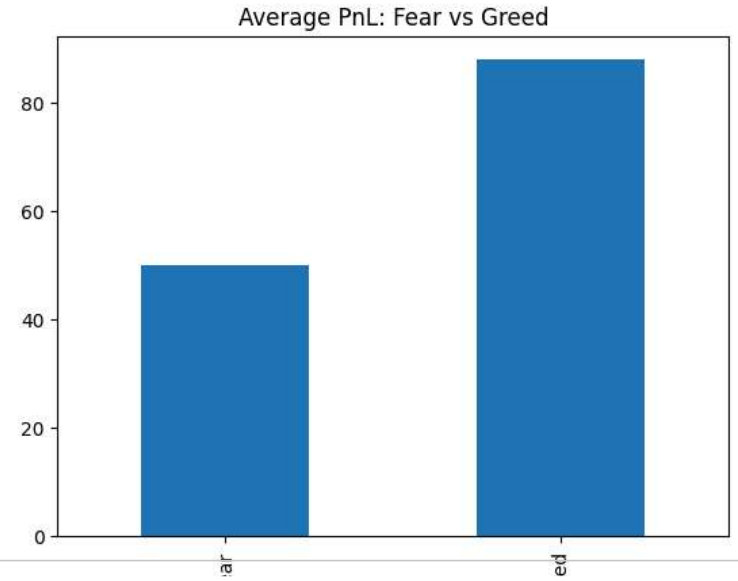
```
analysis = (
    merged
    .dropna(subset=['sentiment_flag'])
    .groupby('sentiment_flag')['Closed PnL']
    .agg(['count', 'mean', 'sum'])
)

analysis.index = analysis.index.map({0: 'Fear', 1: 'Greed'})
analysis
```

sentiment_flag	count	mean	sum
Fear	133871	50.047622	6.699925e+06
Greed	36289	87.894859	3.189617e+06

Next steps: Generate code with analysis | New interactive sheet

```
analysis[['mean']].plot(
    kind='bar',
    title='Average PnL: Fear vs Greed',
    legend=False
)
```

```
<Axes: title={'center': 'Average PnL: Fear vs Greed'}, xlabel='sentiment_flag'>
```



Close

```
# Final Report: Trader Behavior vs Market Sentiment

## Objective
The objective of this analysis was to understand how market
sentiment
(Fear vs Greed) impacts trader performance using historical
trading data
and the Bitcoin Fear & Greed Index.

## Data Description
- Historical trader-level transaction data (Hyperliquid)
- Bitcoin Fear & Greed Index (daily sentiment indicator)

Due to GitHub file size constraints (>25MB), the full historical
dataset
is not included in the repository.

## Methodology
- Cleaned and standardized timestamp formats
- Aggregated trades at daily level
- Merged trading data with sentiment index
- Compared trader performance across Fear and Greed regimes

## Key Findings
- Average Closed PnL is higher during Greed periods
- Fear periods show more conservative trading behavior
- Market sentiment plays a measurable role in trading outcomes

## Conclusion
Market sentiment significantly influences trader behavior and
profitability.
Greed periods are associated with higher average returns, while
Fear periods
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```

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Market sentiment significantly influences trader behavior and profitability. Greed periods are associated with higher average returns, while Fear periods exhibit cautious trading patterns.