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

from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA

# Download daily stock data for AAPL
ticker = "NMR"
start_date = "2023-01-01"
end_date = "2024-12-31"

data = yf.download(ticker, start=start_date, end=end_date,
interval="1d")
data.reset_index(inplace=True)
data.head()
```

```
C:\Users\aarsh\AppData\Local\Temp\ipykernel_27608\1623916390.py:6:
FutureWarning: YF.download() has changed argument auto_adjust default
to True
  data = yf.download(ticker, start=start_date, end=end_date,
interval="1d")
[*********************100%***********************]  1 of 1 completed
```

Price	Date	Close	High	Low	Open	Volume
Ticker		NMR	NMR	NMR	NMR	NMR
0	2023-01-03	3.77	3.80	3.75	3.80	944900
1	2023-01-04	3.82	3.83	3.78	3.79	1391800
2	2023-01-05	3.74	3.76	3.70	3.74	1014600
3	2023-01-06	3.80	3.81	3.69	3.73	1916600
4	2023-01-09	3.79	3.84	3.78	3.83	523800

```
print(data.columns)
```

```
MultiIndex([(  'Date',    ''),
            ( 'Close', 'NMR'),
            (  'High', 'NMR'),
            (   'Low', 'NMR'),
            (  'Open', 'NMR'),
            ('Volume', 'NMR')],
           names=['Price', 'Ticker'])
```

```
# Flatten multi-level columns
data.columns = [col[0] if isinstance(col, tuple) else col for col in
data.columns]

print(data.columns)
```

```
Index(['Date', 'Close', 'High', 'Low', 'Open', 'Volume'],
dtype='object')
```

```
data[["Date", "Open", "Close", "High", "Low"]].isna().sum()
```

```
Date     0
Open     0
Close    0
High     0
Low      0
dtype: int64
```

```
data.dropna(inplace=True)
data.reset_index(drop=True, inplace=True)

# Price based Features
data["daily_return"] = (data["Close"] - data["Open"]) / data["Open"]

data["price_range"] = (data["High"] - data["Low"]) / data["Open"]

data["volatility"] = data[["Open", "High", "Low",
"Close"]].std(axis=1)

data
```

```
          Date  Close  High   Low  Open   Volume  daily_return
price_range  \
0   2023-01-03   3.77  3.80  3.75  3.80   944900     -0.007895
0.013158
1   2023-01-04   3.82  3.83  3.78  3.79  1391800      0.007916
0.013193
2   2023-01-05   3.74  3.76  3.70  3.74  1014600      0.000000
0.016043
3   2023-01-06   3.80  3.81  3.69  3.73  1916600      0.018767
0.032172
4   2023-01-09   3.79  3.84  3.78  3.83   523800     -0.010444
0.015666
..         ...    ...   ...   ...   ...      ...           ...
...
496 2024-12-23   5.77  5.77  5.69  5.69   359100      0.014060
0.014060
497 2024-12-24   5.80  5.80  5.76  5.80   205400      0.000000
0.006897
498 2024-12-26   5.86  5.88  5.81  5.81   377300      0.008606
0.012048
499 2024-12-27   5.86  5.90  5.82  5.89   482500     -0.005093
0.013582
500 2024-12-30   5.83  5.88  5.75  5.81   650300      0.003442
0.022375

     volatility
```

```
0      0.024495
1      0.023805
2      0.025166
3      0.057373
4      0.029439
..          ...
496    0.046188
497    0.020000
498    0.035590
499    0.035940
500    0.053774

[501 rows x 9 columns]
```

```
# Volume based features
data["volume_change"] = data["Volume"].pct_change()

data["volume_5day_avg"] = data["Volume"].rolling(window=5).mean()
data["volume_vs_avg"] = data["Volume"] / data["volume_5day_avg"]

data
```

```
          Date  Close  High   Low  Open   Volume  daily_return
price_range  \
0   2023-01-03   3.77  3.80  3.75  3.80   944900     -0.007895
0.013158
1   2023-01-04   3.82  3.83  3.78  3.79  1391800      0.007916
0.013193
2   2023-01-05   3.74  3.76  3.70  3.74  1014600      0.000000
0.016043
3   2023-01-06   3.80  3.81  3.69  3.73  1916600      0.018767
0.032172
4   2023-01-09   3.79  3.84  3.78  3.83   523800     -0.010444
0.015666
..         ...    ...   ...   ...   ...      ...           ...
...
496 2024-12-23   5.77  5.77  5.69  5.69   359100      0.014060
0.014060
497 2024-12-24   5.80  5.80  5.76  5.80   205400      0.000000
0.006897
498 2024-12-26   5.86  5.88  5.81  5.81   377300      0.008606
0.012048
499 2024-12-27   5.86  5.90  5.82  5.89   482500     -0.005093
0.013582
500 2024-12-30   5.83  5.88  5.75  5.81   650300      0.003442
0.022375

     volatility  volume_change  volume_5day_avg  volume_vs_avg
0      0.024495            NaN              NaN            NaN
1      0.023805       0.472960              NaN            NaN
```

```
2      0.025166      -0.271016              NaN            NaN
3      0.057373       0.889020              NaN            NaN
4      0.029439      -0.726704        1158340.0       0.452199
..          ...            ...              ...            ...
496    0.046188      -0.158819         453480.0       0.791876
497    0.020000      -0.428014         426200.0       0.481933
498    0.035590       0.836904         395360.0       0.954320
499    0.035940       0.278823         370240.0       1.303209
500    0.053774       0.347772         414920.0       1.567290

[501 rows x 12 columns]
```

```
data.dropna(inplace=True)
data.reset_index(drop=True, inplace=True)
data
```

```
          Date  Close  High   Low  Open  Volume  daily_return
price_range  \
0   2023-01-09   3.79  3.84  3.78  3.83  523800     -0.010444
0.015666
1   2023-01-10   3.75  3.76  3.72  3.75  979700      0.000000
0.010667
2   2023-01-11   3.79  3.80  3.77  3.79  758800      0.000000
0.007916
3   2023-01-12   3.87  3.89  3.81  3.82  765800      0.013089
0.020942
4   2023-01-13   3.97  3.97  3.89  3.89  725100      0.020566
0.020566
..         ...    ...   ...   ...   ...     ...           ...
...
492 2024-12-23   5.77  5.77  5.69  5.69  359100      0.014060
0.014060
493 2024-12-24   5.80  5.80  5.76  5.80  205400      0.000000
0.006897
494 2024-12-26   5.86  5.88  5.81  5.81  377300      0.008606
0.012048
495 2024-12-27   5.86  5.90  5.82  5.89  482500     -0.005093
0.013582
496 2024-12-30   5.83  5.88  5.75  5.81  650300      0.003442
0.022375

     volatility  volume_change  volume_5day_avg  volume_vs_avg
0      0.029439      -0.726704        1158340.0       0.452199
1      0.017320       0.870370        1165300.0       0.840728
2      0.012583      -0.225477        1038700.0       0.730529
3      0.038622       0.009225         988940.0       0.774364
4      0.046188      -0.053147         750640.0       0.965976
..          ...            ...              ...            ...
492    0.046188      -0.158819         453480.0       0.791876
493    0.020000      -0.428014         426200.0       0.481933
```

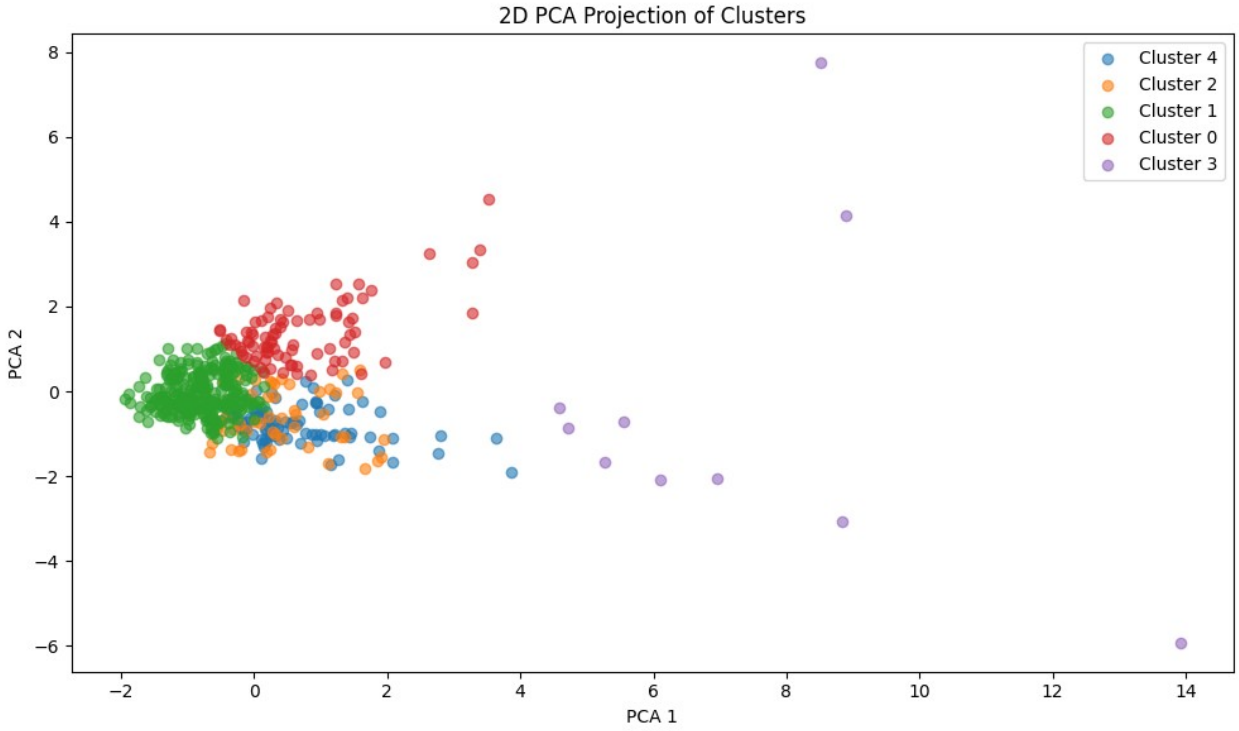
```
494    0.035590       0.836904          395360.0       0.954320
495    0.035940       0.278823          370240.0       1.303209
496    0.053774       0.347772          414920.0       1.567290

[497 rows x 12 columns]
```

```
features = ["daily_return", "price_range", "volatility",
"volume_change"]
X = data[features]

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

kmeans = KMeans(n_clusters=5, random_state=42)
data["cluster"] = kmeans.fit_predict(X_scaled)

sns.countplot(data=data, x="cluster")
plt.title("Cluster Distribution of Trading Days")
plt.show()
```

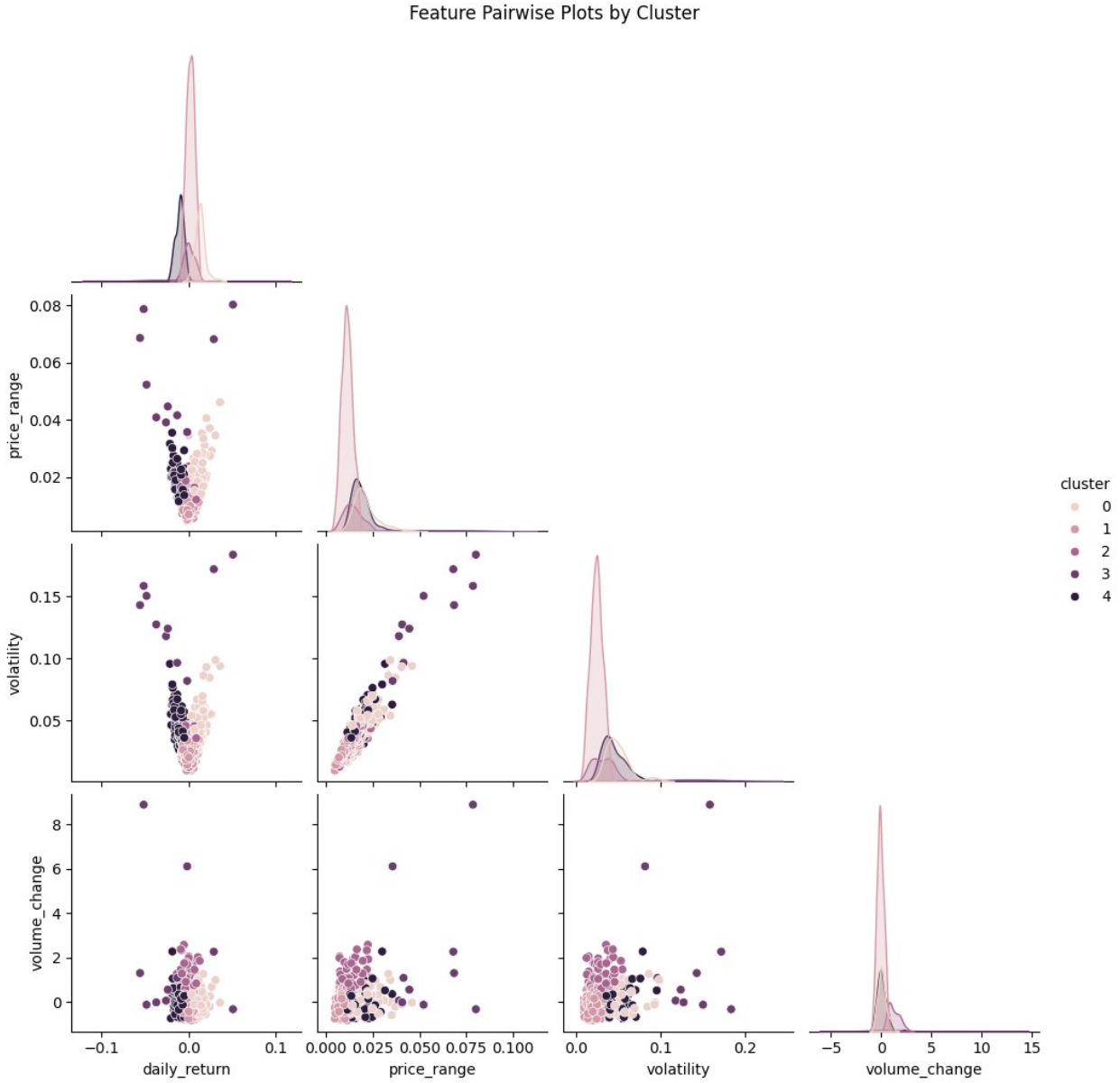

```
data.groupby("cluster")[features].mean().round(3)
```

```
         daily_return  price_range  volatility  volume_change
cluster
0               0.013        0.021       0.049          0.089
1               0.002        0.011       0.024         -0.091
2               0.000        0.014       0.031          1.250
3              -0.018        0.055       0.135          1.980
4              -0.011        0.018       0.044          0.046
```

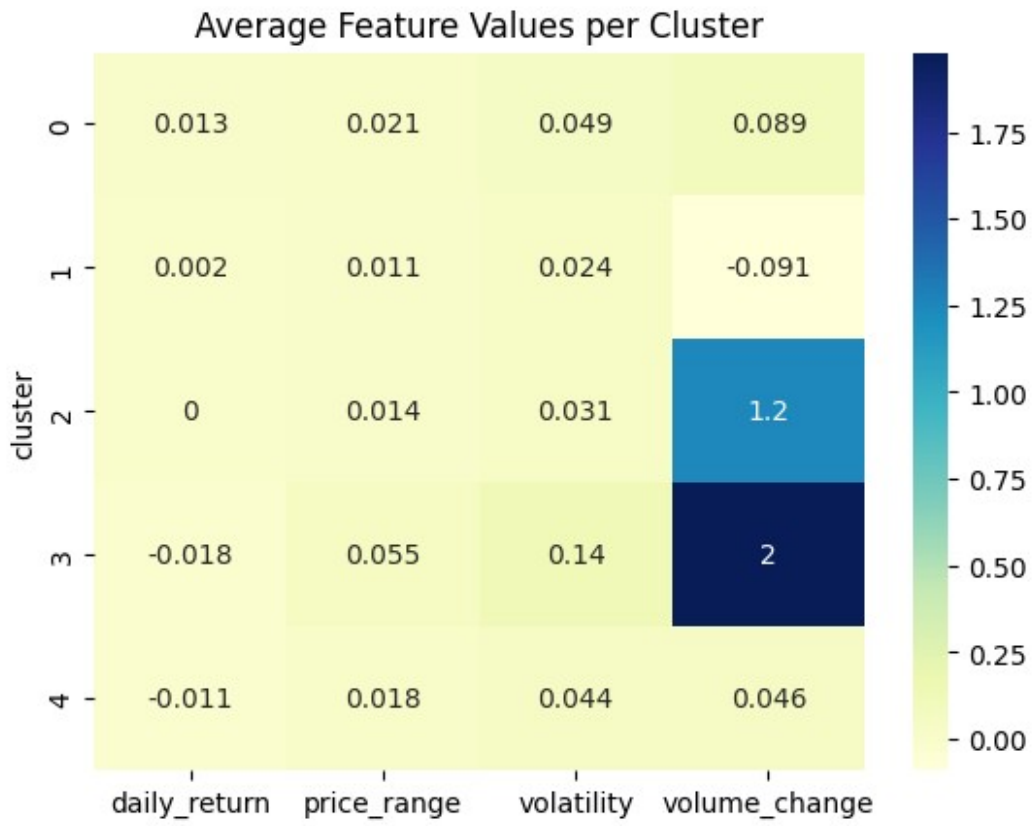
```
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

plt.figure(figsize=(10, 6))
for cluster in data["cluster"].unique():
    plt.scatter(X_pca[data["cluster"] == cluster, 0],
                X_pca[data["cluster"] == cluster, 1],
                label=f"Cluster {cluster}", alpha=0.6)

plt.title("2D PCA Projection of Clusters")
plt.xlabel("PCA 1")
plt.ylabel("PCA 2")
plt.legend()
plt.tight_layout()
plt.show()
```



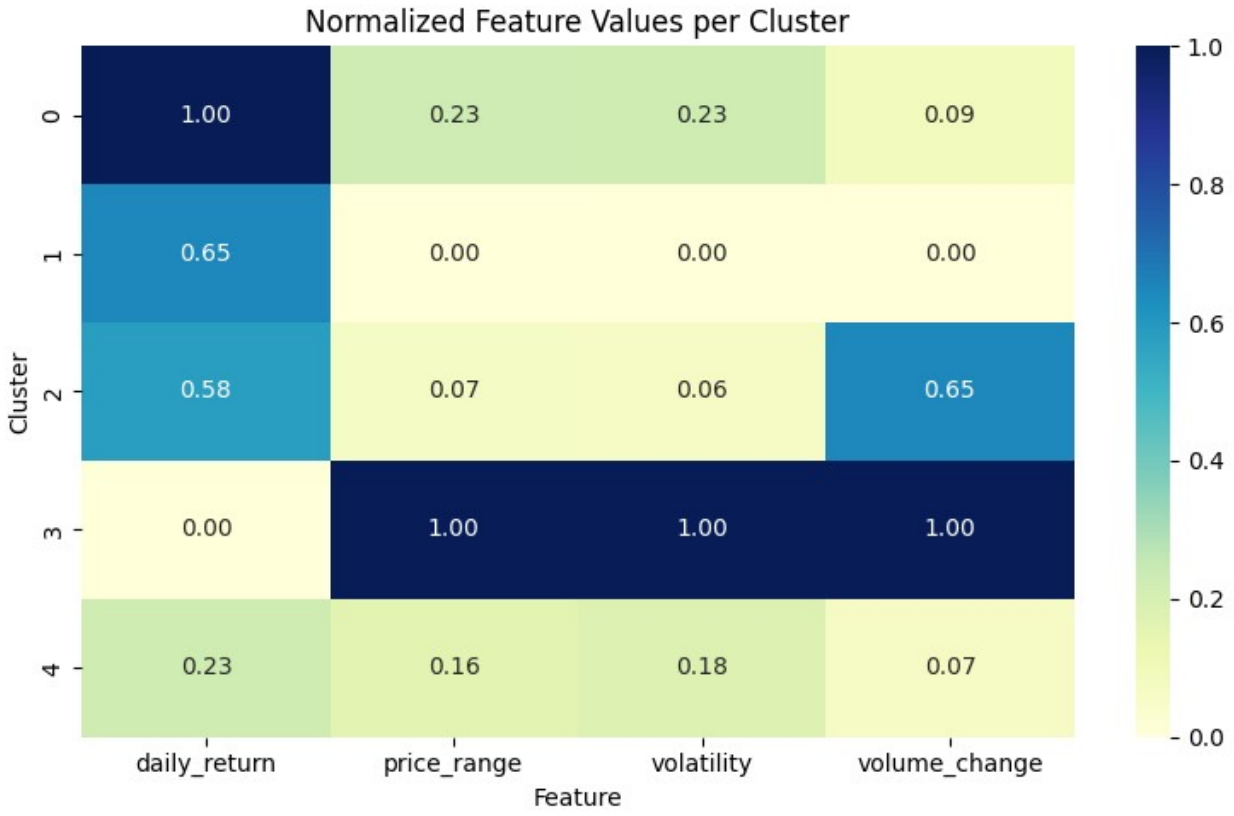

```
sns.pairplot(data[features + ["cluster"]], hue="cluster", corner=True)
plt.suptitle("Feature Pairwise Plots by Cluster", y=1.02)
plt.show()
```




```
cluster_summary = data.groupby("cluster")[features].mean().round(3)
sns.heatmap(cluster_summary, annot=True, cmap="YlGnBu")
plt.title("Average Feature Values per Cluster")
plt.show()
```




```
# Normalize the values for visualization (0 to 1 scale)
scaler = MinMaxScaler()
cluster_summary_normalized = pd.DataFrame(
    scaler.fit_transform(cluster_summary),
    columns=cluster_summary.columns,
    index=cluster_summary.index
)

# Plot the normalized heatmap
plt.figure(figsize=(8, 5))
sns.heatmap(cluster_summary_normalized, annot=True, cmap="YlGnBu",
fmt=".2f")
plt.title("Normalized Feature Values per Cluster")
plt.ylabel("Cluster")
plt.xlabel("Feature")
plt.tight_layout()
plt.show()
```


Normalized Feature Values per Cluster
Cluster
0
1
2
3
4
1.00
0.23
0.23
0.09
0.65
0.00
0.00
0.00
0.58
0.07
0.06
0.65
0.00
1.00
1.00
1.00
0.23
0.16
0.18
0.07
daily_return
price_range
volatility
volume_change
Feature
1.0
0.8
0.6
0.4
0.2
0.0