
Investing in Construction and Infrastructure Companies Including Commercial Aerospace and Defense Industries

There is a recurring need to maintain infrastructure, not only for highways but also for buildings that must meet updated safety codes. Many construction and infrastructure companies can view this as an opportunity to collaborate with cities to develop plans for maintaining commercial buildings and roads. Additionally, investing in the defense and aerospace sectors can support strategic objectives when needed. Specializing and achieving new benchmarks in these industries is equally important, as they will remain significant in the long term, driving both economic and technological progress.

With increasing numbers of retirements in these sectors, it has become even more critical for them to uphold the highest standards of work while addressing workforce shortages. However, these industries are often not seen as lucrative by potential newcomers, leading to recruitment challenges. Recognizing their importance is essential, alongside prioritizing advancements in technology to meet future demands and maintain global competitiveness. This underscores the necessity of securing funding to support these companies, fostering innovation, growth, and the development of a skilled workforce to sustain these pivotal sectors over time.

Why focus on aerospace and defence?

Focusing on aerospace and defense industries is vital due to their significant role in supporting national infrastructure and technological innovation. These sectors contribute to economic stability and advancements in critical technologies. Investments in upgrading aging systems not only enhance operational efficiency but also drive innovation that can benefit other industries. Moreover, understanding the dynamics of these sectors allows for better resource allocation and strategic planning to address evolving global and domestic needs.

Using Cluster Matrices to Study Covariant, Affine Price Behaviors between Construction/Infrastructure Companies and Aerospace/Defence

This study samples the recent price behavior of 10 companies, then traces the covariant, linear behavior, matrix style. Affine, or common mover groups are established, and presented interactively, for the viewer in a visual milieu.

Discussion of data pipeline used, and the subsequent data transformations needed in order to create this affine matrix, as well as the technical tools to facilitate this.

Overview of Data Science Techniques

The pipeline includes downloading data, introducing processing efficiencies, model building and cross validation, and cluster expression. I outline my steps as I take them, to arrive at a matrix of pricing which affords the following advantages.

The experiment was adapted from scikit-learn's own documentation, where the techniques were applied to the US stock market. My rendition creates several departures while adapting the advantage of Varoquaux's pipeline.[1]

1. The data ingest is fast, efficient, updateable and portable. Anyone may use this code to build a working model of US-traded stocks, and add symbols they wish to see, where I have missed them.
2. Data represent public, recently settled trades.
3. Local CPU resources are used in order to use notebook memory efficiently, and leverage local Linux resources.
4. Data remains in perpetuity for the analyst, or it may be rebuilt, using updated, daily trade series.
5. Data is built as a time series, in the OHLC format, where Opening, Closing, High and daily Low prices are located.
6. Clustering is aimed toward predictive use, where clusters can achieve whatever size is needed, to cluster affine, covariant items
7. Every company under consideration is measured for covariance against each other and to locate other trades in the same linear way
8. Sparse Inverse Covariance is the technique used to identify relationships between every item in the Matrix, and thus expose clusters of products, trading similarly. This is a list of connected items, trading conditionally upon the others. Thus the list is a useable, probable list of items which trade in the same way over a week of US business

or items which trade in the same way, over a week or so business.

9. An edge model exposes the borders for classification, and locates clusters at its discretion. Thus, no supervised limits are imposed in cluster formation.
10. Hyperparameters are determined via search with a predetermined number of folds, where each subset is used to locate model parameters, which are averaged at the close of the run.
11. Given the large volume of colinear features, a cross validation technique is used to 'lasso' model features.

Building the Data Science Environment for Linux and Python

Use the following commands to interface with your underlying linux environment. These may not need to be commented out, but will remain necessary each time a new kernel boot, in your notebook, takes place.

```
!pip install yfinance==0.2.40
!pip install vega_datasets
!pip install -U kaleido
```

```
Collecting yfinance==0.2.40
  Downloading yfinance-0.2.40-py2.py3-none-any.whl.metadata (11 kB)
Requirement already satisfied: pandas>=1.3.0 in /usr/local/lib/python3.11/dist-packages (from yfinance==0.2.40) (2.2.2)
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Requirement already satisfied: multitasking>=0.0.7 in /usr/local/lib/python3.11/dist-packages (from yfinance==0.2.40) (0.0.11)
Requirement already satisfied: lxml>=4.9.1 in /usr/local/lib/python3.11/dist-packages (from yfinance==0.2.40) (5.3.0)
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Requirement already satisfied: pytz>=2022.5 in /usr/local/lib/python3.11/dist-packages (from yfinance==0.2.40) (2025.1)
Requirement already satisfied: frozendict>=2.3.4 in /usr/local/lib/python3.11/dist-packages (from yfinance==0.2.40) (2.4.6)
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Requirement already satisfied: beautifulsoup4>=4.11.1 in /usr/local/lib/python3.11/dist-packages (from yfinance==0.2.40) (4.13.3)
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Requirement already satisfied: six>=1.9 in /usr/local/lib/python3.11/dist-packages (from html5lib>=1.1->yfinance==0.2.40) (1.17.0)
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Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-packages (from requests>=2.31->yfinance==0.2.40) (2025.1.31)
Downloading yfinance-0.2.40-py2.py3-none-any.whl (73 kB)
73.5/73.5 kB 2.2 MB/s eta 0:00:00
Installing collected packages: yfinance
  Attempting uninstall: yfinance
    Found existing installation: yfinance 0.2.52
    Uninstalling yfinance-0.2.52:
      Successfully uninstalled yfinance-0.2.52
Successfully installed yfinance-0.2.40
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Collecting kaleido
  Downloading kaleido-0.2.1-py2.py3-none-manylinux1_x86_64.whl.metadata (15 kB)
  Downloading kaleido-0.2.1-py2.py3-none-manylinux1_x86_64.whl (79.9 MB)
79.9/79.9 MB 8.7 MB/s eta 0:00:00
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| Page 1 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 | 34 | 35 | 36 | 37 | 38 | 39 | 40 | 41 | 42 | 43 | 44 | 45 | 46 | 47 | 48 | 49 | 50 | 51 | 52 | 53 | 54 | 55 | 56 | 57 | 58 | 59 | 60 | 61 | 62 | 63 | 64 | 65 | 66 | 67 | 68 | 69 | 70 | 71 | 72 | 73 | 74 | 75 | 76 | 77 | 78 | 79 | 80 | 81 | 82 | 83 | 84 | 85 | 86 | 87 | 88 | 89 | 90 | 91 | 92 | 93 | 94 | 95 | 96 | 97 | 98 | 99 | 100 | 101 | 102 | 103 | 104 | 105 | 106 | 107 | 108 | 109 | 110 | 111 | 112 | 113 | 114 | 115 | 116 | 117 | 118 | 119 | 120 | 121 | 122 | 123 | 124 | 125 | 126 | 127 | 128 | 129 | 130 | 131 | 132 | 133 | 134 | 135 | 136 | 137 | 138 | 139 | 140 | 141 | 142 | 143 | 144 | 145 | 146 | 147 | 148 | 149 | 150 | 151 | 152 | 153 | 154 | 155 | 156 | 157 | 158 | 159 | 160 | 161 | 162 | 163 | 164 | 165 | 166 | 167 | 168 | 169 | 170 | 171 | 172 | 173 | 174 | 175 | 176 | 177 | 178 | 179 | 180 | 181 | 182 | 183 | 184 | 185 | 186 | 187 | 188 | 189 | 190 | 191 | 192 | 193 | 194 | 195 | 196 | 197 | 198 | 199 | 200 | 201 | 202 | 203 | 204 | 205 | 206 | 207 | 208 | 209 | 210 | 211 | 212 | 213 | 214 | 215 | 216 | 217 | 218 | 219 | 220 | 221 | 222 | 223 | 224 | 225 | 226 | 227 | 228 | 229 | 230 | 231 | 232 | 233 | 234 | 235 | 236 | 237 | 238 | 239 | 240 | 241 | 242 | 243 | 244 | 245 | 246 | 247 | 248 | 249 | 250 | 251 | 252 | 253 | 254 | 255 | 256 | 257 | 258 | 259 | 260 | 261 | 262 | 263 | 264 | 265 | 266 | 267 | 268 | 269 | 270 | 271 | 272 | 273 | 274 | 275 | 276 | 277 | 278 | 279 | 280 | 281 | 282 | 283 | 284 | 285 | 286 | 287 | 288 | 289 | 290 | 291 | 292 | 293 | 294 | 295 | 296 | 297 | 298 | 299 | 300 | 301 | 302 | 303 | 304 | 305 | 306 | 307 | 308 | 309 | 310 | 311 | 312 | 313 | 314 | 315 | 316 | 317 | 318 | 319 | 320 | 321 | 322 | 323 | 324 | 325 | 326 | 327 | 328 | 329 | 330 | 331 | 332 | 333 | 334 | 335 | 336 | 337 | 338 | 339 | 340 | 341 | 342 | 343 | 344 | 345 | 346 | 347 | 348 | 349 | 350 | 351 | 352 | 353 | 354 | 355 | 356 | 357 | 358 | 359 | 360 | 361 | 362 | 363 | 364 | 365 | 366 | 367 | 368 | 369 | 370 | 371 | 372 | 373 | 374 | 375 | 376 | 377 | 378 | 379 | 380 | 381 | 382 | 383 | 384 | 385 | 386 | 387 | 388 | 389 | 390 | 391 | 392 | 393 | 394 | 395 | 396 | 397 | 398 | 399 | 400 | 401 | 402 | 403 | 404 | 405 | 406 | 407 | 408 | 409 | 410 | 411 | 412 | 413 | 414 | 415 | 416 | 417 | 418 | 419 | 420 | 421 | 422 | 423 | 424 | 425 | 426 | 427 | 428 | 429 | 430 | 431 | 432 | 433 | 434 | 435 | 436 | 437 | 438 | 439 | 440 | 441 | 442 | 443 | 444 | 445 | 446 | 447 | 448 | 449 | 450 | 451 | 452 | 453 | 454 | 455 | 456 | 457 | 458 | 459 | 460 | 461 | 462 | 463 | 464 | 465 |
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Data Ingest from Public Markets

The free, common Yahoo Finace API is used to download data from all commodities you wish to see studied. This data will be stored persistently next to your notebook in common environments such as Binder.

Please note that if you deploy this notebook in Google Collab that the 37+ files downloaded will be erased between uses, but can be rebuilt easily each time you operate this notebook.

The data you download becomes permanently usable, and the ingest request below can be customized in order to grab more, or less data and at different intervals.[2]

I have included several exceptions to the download and renaming technique, in order to tolerate stocks with differing ticker symbols.

```
import yfinance as yf
from time import time, ctime, clock_gettime
from time import gmtime, time, time_ns

def ifs(input):
    ni = ''
    if input == 'gff':
        input = 'GFF'
        ni = "GF=F"
    elif input == 'zff':
        input = 'ZFF'
        ni = "ZF=F"
    else:
        input = input.upper()
        ins = "="
        before = "F"
        ni = input.replace(before, ins + before , 1)
    print(ni)
    data = yf.download(
        tickers = ni,
        period = "5y",
        interval = "1d",
        group_by = 'ticker',
        auto_adjust = True,
        prepost = True,
        threads = True,
        proxy = None
    )
    epoch = ctime()
    filename = input
    data.to_csv(filename)

#lls #only in jupy
```

Trigger Data Downloads

The following code customizes the stocks under investigation. In order to compare every commodity's price history versus the rest in your matrix, the lengths of the data captures are minimized to the length of the smallest data set. Thus, larger sets are only captured at the length of the smallest set.

The volatility of every price tick is calculated via [close price minus open price].

```
#read in csv data from each commodity capture, gather
#assign 'open' to an array, create df from arrays
import numpy as np
import pandas as pd
from scipy.stats import pearsonr
symbol_dict = {"VLO": "Valero Energy", "XOM": "Exxon Corp", "JPM": "JP Morgan", "TGT": "Target Corp", "INTC": "Intel Corporation", "AMZN": "Amazon.com, Inc.", "RTX": "Raytheon Technologies Coi

sym, names = np.array(sorted(symbol_dict.items())).T

for i in sym:    #build all symbol csvs, will populate/appear in your binder. Use linux for efficient dp
    ifs(i)

quotes = []
lens = []
for symbol in sym:
    symbol = symbol.upper()
    t = pd.read_csv(symbol)
    lens.append(t.shape[0])
mm = np.amin(lens)-1
print("min length of data: ",mm)

for symbol in sym:
    symbol = symbol.upper()
    t = pd.read_csv(symbol)
    t= t.truncate(after=mm)
    quotes.append(t)
mi = np.vstack([q["Close"] for q in quotes]) #min
ma = np.vstack([q["Open"] for q in quotes]) #max

volatility = ma - mi
```

```
AMZN
[*****100%*****] 1 of 1 completed
HD
[*****100%*****] 1 of 1 completed
INTC
[*****100%*****] 1 of 1 completed
JPM
[*****100%*****] 1 of 1 completed
LMT
[*****100%*****] 1 of 1 completed
RTX
[*****100%*****] 1 of 1 completed
TGT
[*****100%*****] 1 of 1 completed
VLO
[*****100%*****] 1 of 1 completed
XOM
[*****100%*****] 1 of 1 completed
min length of data: 1257
```

Data Format

After downloading this massive store of data, you should click on a file, in your project. Using the file browser, you will see a large quantity of new files.

When you open one, you will see the rows of new data.

Cross Validate for Optimal Parameters: the Lasso

Varoquaux's pipeline involves steps in the following two cells.

A set of clusters is built using a set of predefined edges, called the edge model. The volatility of every OHLC tick is fed into the edge model, in order to establish a covariance to each other.

The advantages of the Graphical Lasso model is that a cross validated average set of hyperparameters is located, then applied to cluster each stock. Thus, every stock is identified with other stockss which move in tandem, together, over seven days. I print the alpha edges below, and visualize this group.

Depending upon the markets when you run this study, more intensive clustering may take place at either end of the spectrum. This exposes the covariance between different groups, while exposing outlier clusters.

Using the Interactive Graph

Feel free to move your mouse into the graph, then roll your mouse. This will drill in/out and allow you to hover over data points. They will map to the edges of the clusters, under investigation.

```
from sklearn import covariance
import altair as alt
alphas = np.logspace(-1.5, 1, num=15)
edge_model = covariance.GraphicalLassoCV(alphas=alphas)
X = volatility.copy().T
X /= X.std(axis=0)
l = edge_model.fit(X)
n= []
print(type(l.alphas))
for i in range(len(l.alphas)):
    print(l.alphas[i])
    dict = {"idx":i , "alpha":l.alphas[i]}
    n.append(dict)

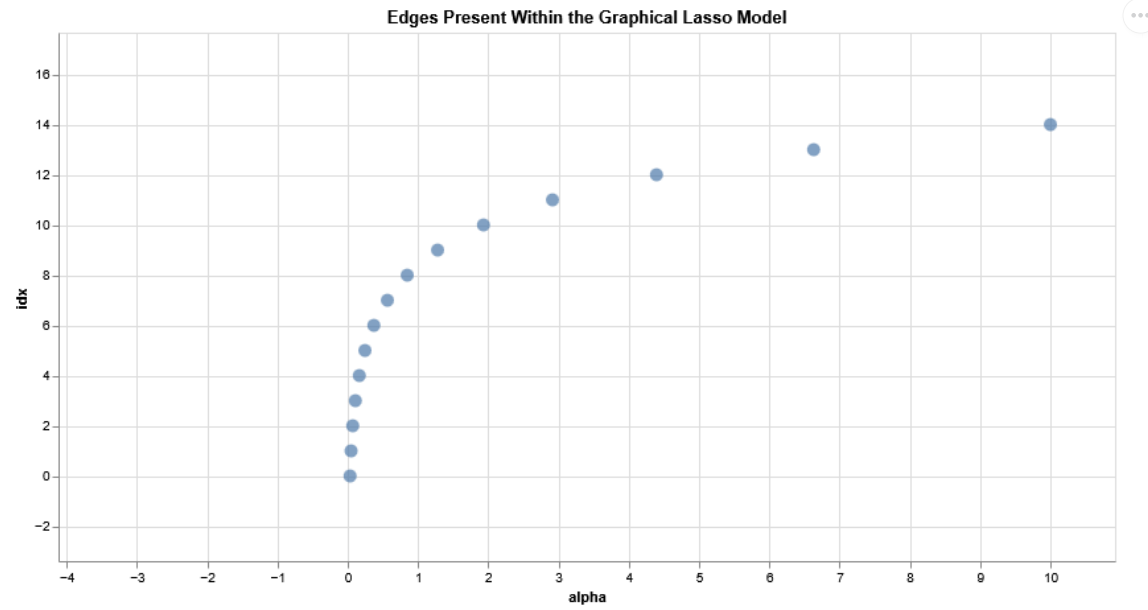
dd = pd.DataFrame(n)
alt.Chart(dd).mark_point(filled=True, size=100).encode(
    y=alt.Y('idx'),
    x=alt.X('alpha'), tooltip=[ 'alpha'],).properties(
        width=800,
        height=400,
        title="Edges Present Within the Graphical Lasso Model"
    ).interactive()

<class 'numpy.ndarray'>
0.03162277660168379
0.047705826961439296
0.07196856730011521
0.10857111194022041
0.16378937069540642
0.2470911227985605
0.372759372031494
0.5623413251903491
0.8483428982440722
1.279802213997954
- -----
```

```

1.93069//288832505
2.9126326549087382
4.39397056076079
6.628703161826448
10.0

```



Defining cluster Membership, by Covariant Affinity

Clusters of covariant, affine moving stocks are established. This group is then passed into a dataframe so that the buckets of symbols can become visible.

```

import pandas as pd
import numpy as np

# Example setup (replace with your data)
clusters = 3
names = np.array(["AMZN", "HD", "INTC", "TGT"])
labels = np.array([0, 0, 1, 2]) # Example labels

# Initialize an empty DataFrame
gdf = pd.DataFrame(columns=["cluster", "symbols", "size", "names"])

# Populate the DataFrame using a loop
for i in range(clusters):
    l = names[labels == i] # Adjust logic if needed
    ss = np.array(names)[labels == i]
    cluster_dict = {"cluster": (i + 1), "symbols": l, "size": len(l), "names": ss}
    gdf = pd.concat([gdf, pd.DataFrame([cluster_dict]), ignore_index=True)

print(gdf.head(15))

```

| | cluster | symbols | size | names |
|---|---------|------------|------|------------|
| 0 | 1 | [AMZN, HD] | 2 | [AMZN, HD] |
| 1 | 2 | [INTC] | 1 | [INTC] |
| 2 | 3 | [TGT] | 1 | [TGT] |

Visualizing cluster and affine securities, by volatility

The interactive graphic requires the user to hover over each dot, in teh scatter chart. The size of the security cluster pushes it to the top, where the user can study the members, whose prices move in covariant fashion.

I have experimented with laying the text of the securities cluster over the dots, but I find that the above table is most helpful, in identifying markets which move in tandem, and with similar price graphs. Also, as groups expand and contract, overlaying text on the chart below may prevent certain clusters from appearing. I appreciate spacing them out, and not congesting the chart.

The user is free to study where his or her chosen security may sit, in close relation to other globally relevant securities.

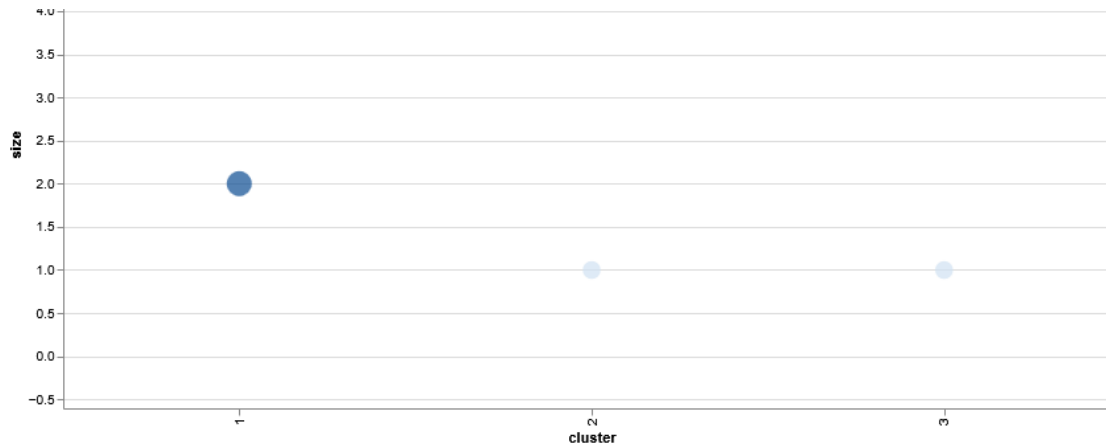
```
for i in gdf['cluster']:
    print("cluster ",i)
    d = gdf[gdf['cluster'].eq(i)]
    for j in d.names:
        print(j, ", ")

cluster 1
['AMZN' 'HD'] ,
cluster 2
['INTC'] ,
cluster 3
['TGT'] ,

import altair as alt
def runCluster():
    c = alt.Chart(gdf).mark_circle(size=60).encode(
        x= alt.X('cluster:N'),
        y= alt.Y('size:Q'),
        color='size:Q',
        tooltip=['names'],
        size=alt.Size('size:Q')
    ).properties(
        width=800,
        height=400,
        title="Top Global Stocks, Clustered by Affine Covariance"
    ).interactive()
    #.configure_title("Top Global Stocks, Clustered by Affine Covariance")

    chart =c
    return chart
runCluster()
```





References

1. Gael Varoquaux. Visualizing the Stock Market Structure. Scikit-Learn documentation pages, https://scikit-learn.org/stable/auto_examples/applications/plot_stock_market.html
2. Ran Aroussi. YFinance API documents. <https://github.com/ranaroussi/yfinance>
3. The Altair Charting Toolkit. <https://altair-viz.github.io/index.html>

```
!pip install plotly
```

```
Requirement already satisfied: plotly in /usr/local/lib/python3.11/dist-packages (5.24.1)
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.11/dist-packages (from plotly) (9.0.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.11/dist-packages (from plotly) (24.2)
```

```
import plotly.graph_objects as go
import pandas as pd
from datetime import datetime
```

```
df_symbol = pd.read_csv('AMZN') #no .csv
```

```
df_symbol.columns
```

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

```
df_symbol.head(3)
```

| | Date | Open | High | Low | Close | Volume | |
|---|------------|------------|------------|------------|------------|----------|--|
| 0 | 2020-02-13 | 107.249496 | 108.514000 | 107.099998 | 107.493500 | 60636000 | |
| 1 | 2020-02-14 | 107.783997 | 107.952003 | 106.294502 | 106.743500 | 52124000 | |
| 2 | 2020-02-18 | 106.250999 | 108.303497 | 106.205498 | 107.783501 | 58912000 | |

Next steps:

[Generate code with df_symbol](#)

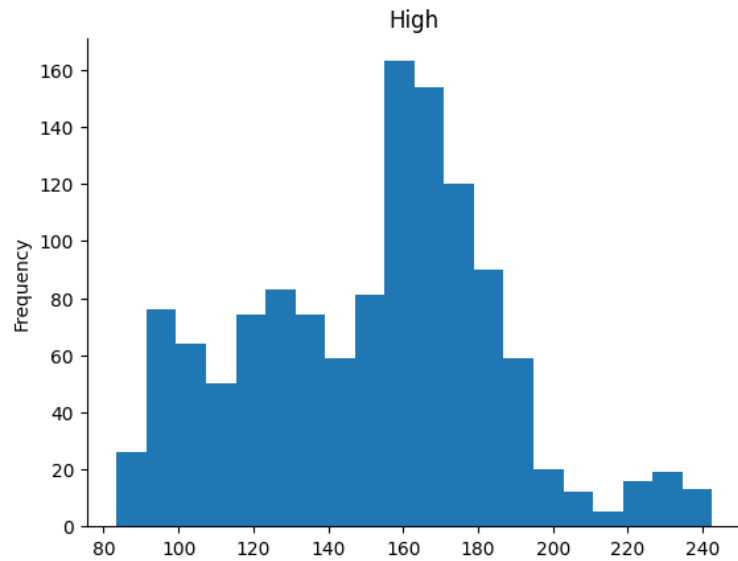
[View recommended plots](#)

[New interactive sheet](#)

✓ High

```
# @title High
```

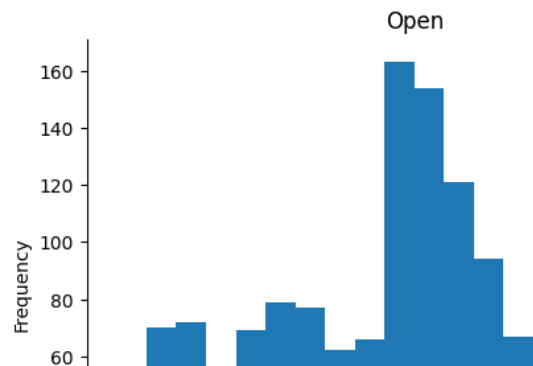
```
from matplotlib import pyplot as plt
df_symbol['High'].plot(kind='hist', bins=20, title='High')
plt.gca().spines[['top', 'right',]].set_visible(False)
```

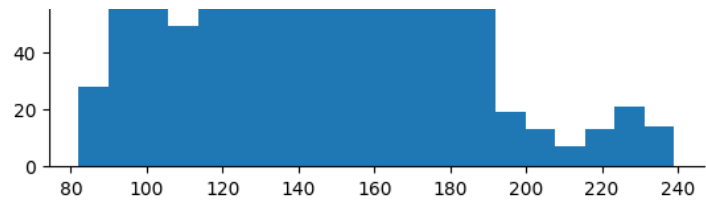


✓ Open

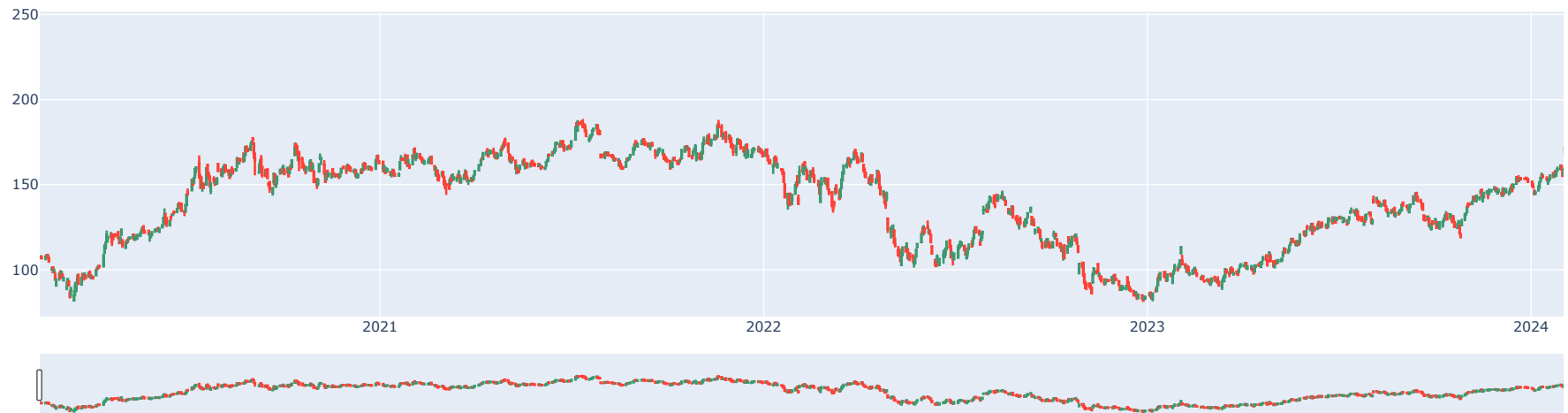
```
# @title Open
```

```
from matplotlib import pyplot as plt
df_symbol['Open'].plot(kind='hist', bins=20, title='Open')
plt.gca().spines[['top', 'right',]].set_visible(False)
```





```
fig = go.Figure(data=[go.Candlestick(x=df_symbol['Date'],
    open=df_symbol['Open'],
    high=df_symbol['High'],
    low=df_symbol['Low'],
    close=df_symbol['Close'])])
fig.show()
```



```
import pandas as pd

# Define ticker symbols
tickers = ["LMT", "VLO", "RTX", "XOM", "INTC", "HD"]

# Initialize empty DataFrame
df2 = pd.DataFrame()

# Loop through each ticker and merge data
for ticker in tickers:
    temp_df = pd.read_csv(ticker, usecols=["Date", "Close"]) # Read CSV file
    temp_df.rename(columns={"Close": ticker}, inplace=True) # Rename Close column to ticker symbol
```

```
temp_df.rename(columns={ 'Close' : 'ticker'}, inplace=True) # Rename Close column to ticker symbol

if df2.empty:
    df2 = temp_df # First DataFrame sets the structure
else:
    df2 = pd.merge(df2, temp_df, on="Date", how="inner") # Merge on 'Date'

# Convert 'Date' to datetime format
df2["Date"] = pd.to_datetime(df2["Date"])

# Display the first few rows
print(df2.head())
```

| | Date | LMT | VLO | RTX | XOM | INTC | \ |
|---|------------|------------|-----------|-----------|-----------|-----------|---|
| 0 | 2020-02-13 | 380.301697 | 67.826462 | 85.456184 | 48.064716 | 59.781246 | |
| 1 | 2020-02-14 | 383.057495 | 66.967499 | 85.679527 | 47.843838 | 59.630547 | |
| 2 | 2020-02-18 | 381.045258 | 66.870247 | 84.462402 | 47.236416 | 58.628872 | |
| 3 | 2020-02-19 | 380.109192 | 67.445618 | 84.127411 | 47.599285 | 59.488716 | |
| 4 | 2020-02-20 | 372.664185 | 68.207329 | 83.691910 | 47.220642 | 58.017227 | |

| | HD |
|---|------------|
| 0 | 214.849365 |
| 1 | 217.216293 |
| 2 | 216.250000 |
| 3 | 215.984116 |
| 4 | 218.980392 |

```
df2.columns
```

```
Index(['Date', 'LMT', 'VLO', 'RTX', 'XOM', 'INTC', 'HD'], dtype='object')
```

```
df2.head(2)
```

| | Date | LMT | VLO | RTX | XOM | INTC | HD |
|---|------------|------------|-----------|-----------|-----------|-----------|------------|
| 0 | 2020-02-13 | 380.301697 | 67.826462 | 85.456184 | 48.064716 | 59.781246 | 214.849365 |
| 1 | 2020-02-14 | 383.057495 | 66.967499 | 85.679527 | 47.843838 | 59.630547 | 217.216293 |

Next steps: [Generate code with df2](#) [View recommended plots](#) [New interactive sheet](#)

```
df_symbol.columns
```

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

```
df_symbol['Close']
```

| | Close |
|---|------------|
| 0 | 107.493500 |
| 1 | 106.743500 |
| 2 | 107.783501 |
| 3 | 108.511002 |
| 4 | 107.654000 |

```

...
1253 229.149994
1254 233.139999
1255 232.759995
1256 228.929993
1257 228.994995
1258 rows × 1 columns

```

dtype: float64

```

# Using plotly.express
import plotly.express as px
fig = px.line(df_symbol, x='Date', y="Close") #contains daily price series
fig.show()

```



✓ Plotting the Clustered Stocks

```

#generate a Date column in gdf
def getDateColumn():
    df = pd.read_csv('LMT') #CHOOSE an equity or vehicle for which you possess a Date index

```

```

return df['Date'] #pandas series

symUpper = [x.upper() for x in sym] #make all symbols in sym to uppercase
# print(symUpper)
gdf = pd.DataFrame(columns=symUpper) #form a new global dataframe, gdf, for purpose of graphing
gdf['Date'] = getDateColumn() #get a common index for dates, for every commodity or equity
for i in range(len(symUpper)): #iterate the length of the uppercase symbols
    df_x = pd.read_csv( symUpper[i]) #create one dataframe to hold the csv contents
    gdf[symUpper[i]] = df_x['Close'] #extract the price series from the 'Closed' column
print(gdf.head(3)) #print the resulting top three rows from the new gdf
# print(gdf.columns)

```

| | AMZN | HD | INTC | JPM | LMT | RTX \ |
|---|------------|------------|-----------|------------|------------|-----------|
| 0 | 107.493500 | 214.849365 | 59.781246 | 119.475555 | 380.301697 | 85.456184 |
| 1 | 106.743500 | 217.216293 | 59.630547 | 119.111641 | 383.057495 | 85.679527 |
| 2 | 107.783501 | 216.250000 | 58.628872 | 117.534569 | 381.045258 | 84.462402 |

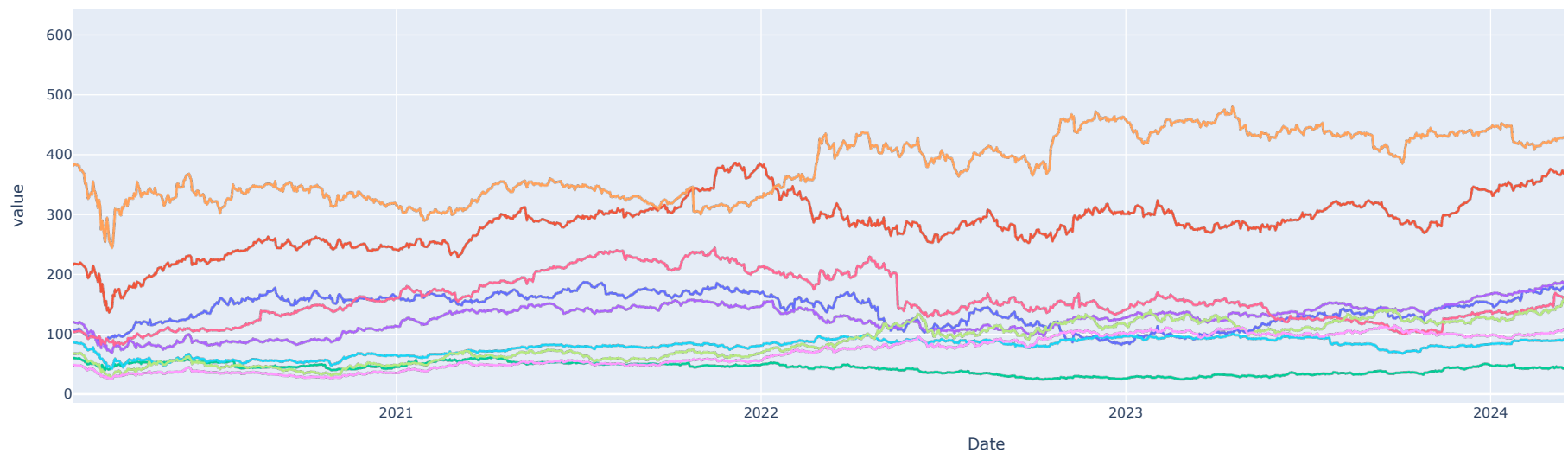
| | TGT | VLO | XOM | Date |
|---|------------|-----------|-----------|------------|
| 0 | 104.469345 | 67.826462 | 48.064716 | 2020-02-13 |
| 1 | 103.012001 | 66.967499 | 47.843838 | 2020-02-14 |
| 2 | 104.664177 | 66.870247 | 47.236416 | 2020-02-18 |

```

fig = px.line(gdf[(gdf["Date"] >= "2020-01-01") & (gdf["Date"] <= "2025-2-1")],
              x="Date", y=gdf.columns,
              hover_data={"Date": "%B %d, %Y"},
              title='Study of Defence, Service, and Infrastructure Sectors in the Market')
fig.show()

```

Study of Defence, Service, and Infrastructure Sectors in the Market



```
gdf.columns

Index(['AMZN', 'HD', 'INTC', 'JPM', 'LMT', 'RTX', 'TGT', 'VLO', 'XOM', 'Date'], dtype='object')

type(gdf.columns)

pandas.core.indexes.base.Index
```

Market Trends Over the Past Five Years

The dataset visualizes market trends from 2020 to 2025, highlighting movements in the defense, service, and energy sectors. Each stock follows its own volatility pattern, reflecting broader economic shifts and sector-specific catalysts.

Amazon (AMZN) and Home Depot (HD) stand out as top performers, with AMZN breaking past 600. Their steady upward trajectory suggests resilience in consumer demand and e-commerce dominance. In contrast, Lockheed Martin (LMT), JPMorgan (JPM), and Raytheon (RTX) display stable growth, moving in tandem. This clustering indicates institutional consistency, with these stocks likely benefiting from defense contracts and financial sector stability.

Energy stocks like Exxon Mobil (XOM) and Valero (VLO) exhibit higher volatility, reacting more to external forces such as oil prices and global production constraints. Unlike the technology and defense sectors, these stocks remain more sensitive to macroeconomic events, resulting in cyclical price swings rather than sustained upward trends.

A key shift occurs post-2023, where AMZN and HD diverge from the broader pack, signaling a possible sectoral decoupling. Defense-related stocks maintain a strong correlation, reinforcing their position as institutional holdings. Overall, we are starting to see a decreasing trend in price movement in early 2025. We will need to wait and see during the next FOMC meeting regarding interest rates.