

# report

June 25, 2024

## 1 Global Stock Market Analytics

in this project we will look at predicting the open direction of the Nifty 50 index by looking at other indices and indicators. We will break the project up into three parts:

- preparing the master data from the global indices
- predictive modelling of open direction of Nifty 50
- sentiment analysis of X / Twitter data relating to Nifty 50

### 1.1 Prepare the Master Data

we begin by preparing the master data that we will be working with. We import the libraries we will be using, and declare some constants.

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

import statsmodels.api as sm
import yfinance as yf
import ta

from scipy import stats

from statsmodels.api import Logit
from statsmodels.stats.outliers_influence import variance_inflation_factor

from sklearn.metrics import classification_report, roc_curve, roc_auc_score
from sklearn.model_selection import train_test_split

plt.style.use("ggplot")
sns.set_style("darkgrid")
sns.set_context("paper")

INDICES = ['NSEI', 'DJI', 'IXIC', 'HSI', 'N225', 'GDAXI', 'VIX']
```

```
COLUMNS = [f"{index}_DAILY_RETURNS" for index in INDICES]
```

next, we declare a function that we will use to download the OHLC data:

```
[ ]: def retrieve_data(index, start_date = '2017-12-1', end_date = '2024-1-31',  
    progress = False):  
    data = yf.download(f'^{index}', start_date, end_date, progress = progress)  
  
    # create daily returns for each index  
    data['Daily Returns'] = data.Close.pct_change() * 100  
  
    # rename columns - prefix with index name  
    data.columns = ["_".join(c.upper() for c in column.split()) for column in_  
    data.columns]  
    data.columns = [f"{index}_{column}" for column in data.columns]  
  
    return data
```

next, we...

```
[ ]: def test_normality(data, column_name, index_name):  
    print()  
    print(f"\t Index {index_name}")  
    print(f"\tColumn {column_name}")  
    print()  
  
    data = data[column_name].dropna()  
  
    if data.shape[0] < 50:  
        print("\t      Shapiro-Wilks Test:")  
        result = stats.shapiro(data)  
    else:  
        print("\tKolmogorov-Smirnov Test:")  
        result = sm.stats.diagnostic.lilliefors(data)  
  
    print(f"\t      p-value: {result[1]}")  
  
    if result[1] < 0.05:  
        print("\treject null hypothesis - data is not drawn from a normal_  
    distribution")  
    else:  
        print("\tfail to reject null hypothesis - data is drawn from a normal_  
    distribution")  
  
    print()
```

next, we...

```
[ ]: def qq_plots(data, title, count = 6):
    fig, axes = plt.subplots(3, 2, sharex = True, figsize = (16, 12))
    fig.suptitle(title)

    for index in range(count):
        axes[index // 2, index % 2].set_title(INDICES[index])
        sm.graphics.qqplot(data[index][COLUMNS[index]].dropna(), line = "45",
        fit = True, ax = axes[index // 2, index % 2])
        axes[index // 2, index % 2].set_xlabel("")
```

next, we...

```
[ ]: def merge_data(data, start_date = '2018-01-02', end_date = '2023-12-29'):
    # merge data with outer join
    merged = pd.concat(data, axis = 1)

    # impute missing data using LOCF (forward fill)
    merged.ffill(inplace = True)

    # add indicators for MONTH, QUARTER, and YEAR
    merged['MONTH'] = merged.index.month
    merged['QUARTER'] = merged.index.quarter
    merged['YEAR'] = merged.index.year

    return merged[start_date:end_date]
```

next, we...

```
[ ]: data = [retrieve_data(index) for index in INDICES]
```

next, we...

```
[ ]: for d, c, i in zip(data, COLUMNS, INDICES):
    # check daily returns follows Normal distribution
    test_normality(d, c, i)
```

Index NSEI  
Column NSEI\_DAILY\_RETURNS

Kolmogorov-Smirnov Test:  
p-value: 0.00099999999999998899  
reject null hypothesis - data is not drawn from a normal distribution

Index DJI  
Column DJI\_DAILY\_RETURNS

Kolmogorov-Smirnov Test:

```
p-value: 0.0009999999999998899
reject null hypothesis - data is not drawn from a normal distribution
```

```
Index IXIC
Column IXIC_DAILY_RETURNS
```

```
Kolmogorov-Smirnov Test:
p-value: 0.0009999999999998899
reject null hypothesis - data is not drawn from a normal distribution
```

```
Index HSI
Column HSI_DAILY_RETURNS
```

```
Kolmogorov-Smirnov Test:
p-value: 0.0009999999999998899
reject null hypothesis - data is not drawn from a normal distribution
```

```
Index N225
Column N225_DAILY_RETURNS
```

```
Kolmogorov-Smirnov Test:
p-value: 0.0009999999999998899
reject null hypothesis - data is not drawn from a normal distribution
```

```
Index GDAXI
Column GDAXI_DAILY_RETURNS
```

```
Kolmogorov-Smirnov Test:
p-value: 0.0009999999999998899
reject null hypothesis - data is not drawn from a normal distribution
```

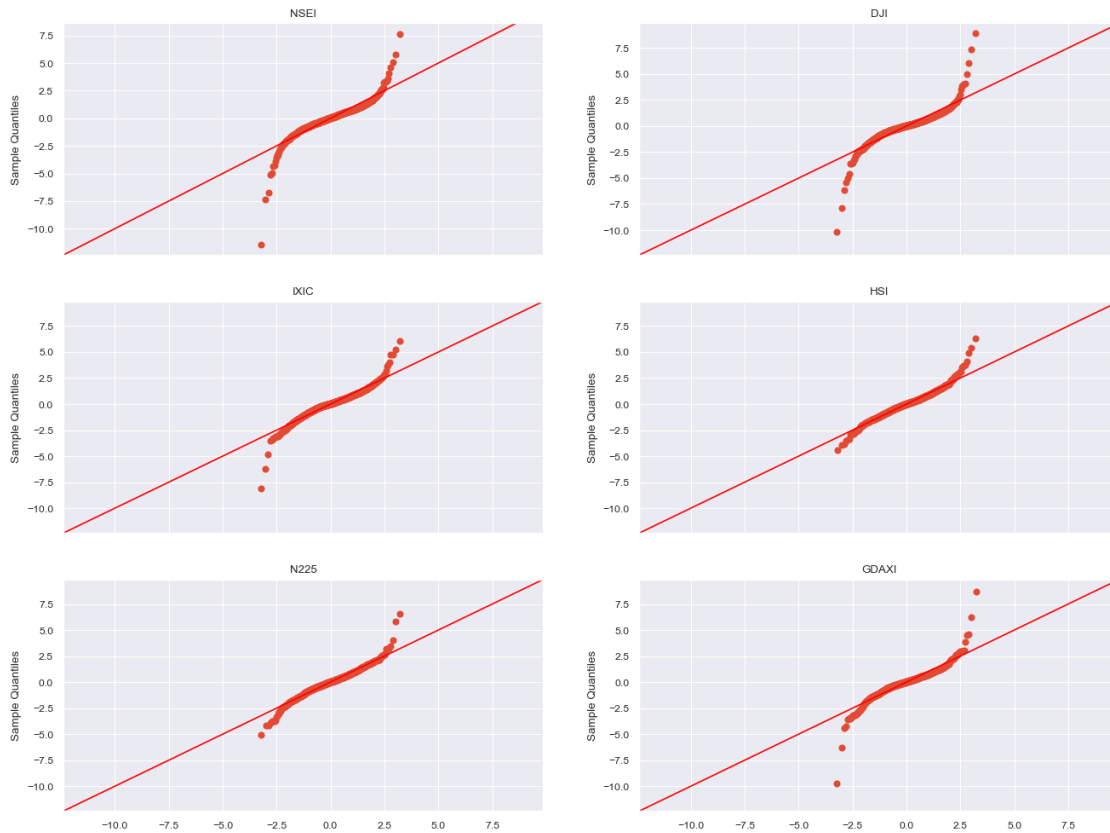
```
Index VIX
Column VIX_DAILY_RETURNS
```

```
Kolmogorov-Smirnov Test:
p-value: 0.0009999999999998899
reject null hypothesis - data is not drawn from a normal distribution
```

next, we...

```
[ ]: # check daily returns follows Normal distribution
qq_plots(data, "Q-Q Plots of Daily Returns")
```

Q-Q Plots of Daily Returns



next, we...

```
[ ]: master = merge_data(data)
```

at which point we have our master data

```
[ ]: CONDITIONS = [(master.index <= '2020-01-30'), ('2022-05-05' <= master.index)]
CHOICES      = ['PRE_COVID', 'POST_COVID']
```

next, we...

```
[ ]: master['PANDEMIC'] = np.select(CONDITIONS, CHOICES, 'COVID')
master['PANDEMIC'] = pd.Categorical(master['PANDEMIC'], categories = _
    ↳ ['PRE_COVID', 'COVID', 'POST_COVID'], ordered = True)
```

next, we...

```
[ ]: master["NSEI_OPEN_DIR"] = np.where(master["NSEI_OPEN"] > master["NSEI_CLOSE"].
    ↳ shift(), 1, 0)
```

next, we...

```
[ ]: def performance_analytics_tables(data, group_by, count = 6):
    for index in range(count):
        table = data.groupby(group_by, observed = False)[COLUMNS[index]].
        ↪agg(['count', 'mean', 'std', 'var'])
        print(f"\n{INDICES[index]}\n\n{table}\n\n")
```

next, we...

```
[ ]: def performance_analytics_box_plots(data, group_by, title, count = 6):
    fig, axes = plt.subplots(3, 2, sharex = True, figsize = (16, 12))
    fig.suptitle(title)

    for index in range(count):
        axes[index // 2, index % 2].set_title(INDICES[index])
        sns.boxplot(x = data[group_by], y = data[COLUMNS[index]], ax =
        ↪axes[index // 2, index % 2])
        axes[index // 2, index % 2].set_xlabel("")
```

next, we...

```
[ ]: def performance_analytics_bar_plots(data, group_by, title, count = 6, aggfunc =
    ↪"median"):
    fig, axes = plt.subplots(3, 2, sharex = True, figsize = (16, 12))
    fig.suptitle(title)

    for index in range(count):
        axes[index // 2, index % 2].set_title(INDICES[index])
        table = data.groupby(group_by, observed = False)[COLUMNS[index]].
        ↪agg([aggfunc])
        sns.barplot(x = table.index, y = table[aggfunc], ax = axes[index // 2,
        ↪index % 2])
        axes[index // 2, index % 2].set_xlabel("")
```

next, we...

```
[ ]: def performance_analytics_heat_maps(data, group_by, title, column = "QUARTER",
    ↪count = 6, aggfunc = "median"):
    fig, axes = plt.subplots(3, 2, sharex = True, figsize = (16, 12))
    fig.suptitle(title)

    for index in range(count):
        axes[index // 2, index % 2].set_title(INDICES[index])
        table = pd.pivot_table(data, values = COLUMNS[index], index =
        ↪[group_by], columns = [column], aggfunc = aggfunc, observed = False)
        sns.heatmap(table, ax = axes[index // 2, index % 2])
        axes[index // 2, index % 2].set_xlabel("")
```

next, we...

```
[ ]: def correlation_matrix(data):
    plt.figure(figsize = (9, 6))
    matrix = data[COLUMNS[:-1]].corr()

    ax = sns.heatmap(matrix, annot = True)
    ax.set_xticklabels(
        ax.get_xticklabels(),
        rotation = 30,
        horizontalalignment = "right"
    )
```

next, we...

```
[ ]: performance_analytics_tables(master, "YEAR")
```

NSEI

	count	mean	std	var
YEAR				
2018	260	0.011858	0.804320	0.646931
2019	260	0.061655	0.862269	0.743508
2020	262	0.059276	2.003775	4.015114
2021	261	0.093951	0.979932	0.960268
2022	260	0.054513	1.096428	1.202155
2023	260	0.079254	0.620049	0.384461

DJI

	count	mean	std	var
YEAR				
2018	260	-0.034755	1.142622	1.305584
2019	260	0.098867	0.783563	0.613972
2020	262	0.056509	2.277254	5.185886
2021	261	0.074976	0.772875	0.597336
2022	260	-0.024515	1.237294	1.530896
2023	260	0.059685	0.708875	0.502504

IXIC

	count	mean	std	var
YEAR				
2018	260	-0.020231	1.329736	1.768199
2019	260	0.132933	0.974714	0.950068

2020	262	0.170412	2.199609	4.838279
2021	261	0.095541	1.123517	1.262289
2022	260	-0.124394	2.000332	4.001327
2023	260	0.156594	1.084932	1.177078

HSI

	count	mean	std	var
YEAR				
2018	260	-0.034949	1.243767	1.546955
2019	260	0.033120	0.980864	0.962095
2020	262	0.026129	1.444816	2.087493
2021	261	-0.028481	1.262121	1.592949
2022	260	-0.020744	2.054467	4.220835
2023	260	-0.052676	1.408653	1.984302

N225

	count	mean	std	var
YEAR				
2018	260	-0.047420	1.198187	1.435653
2019	260	0.065377	0.860102	0.739776
2020	262	0.013181	1.614888	2.607863
2021	261	0.028503	1.152231	1.327636
2022	260	-0.036233	1.261568	1.591553
2023	260	0.105084	0.998616	0.997234

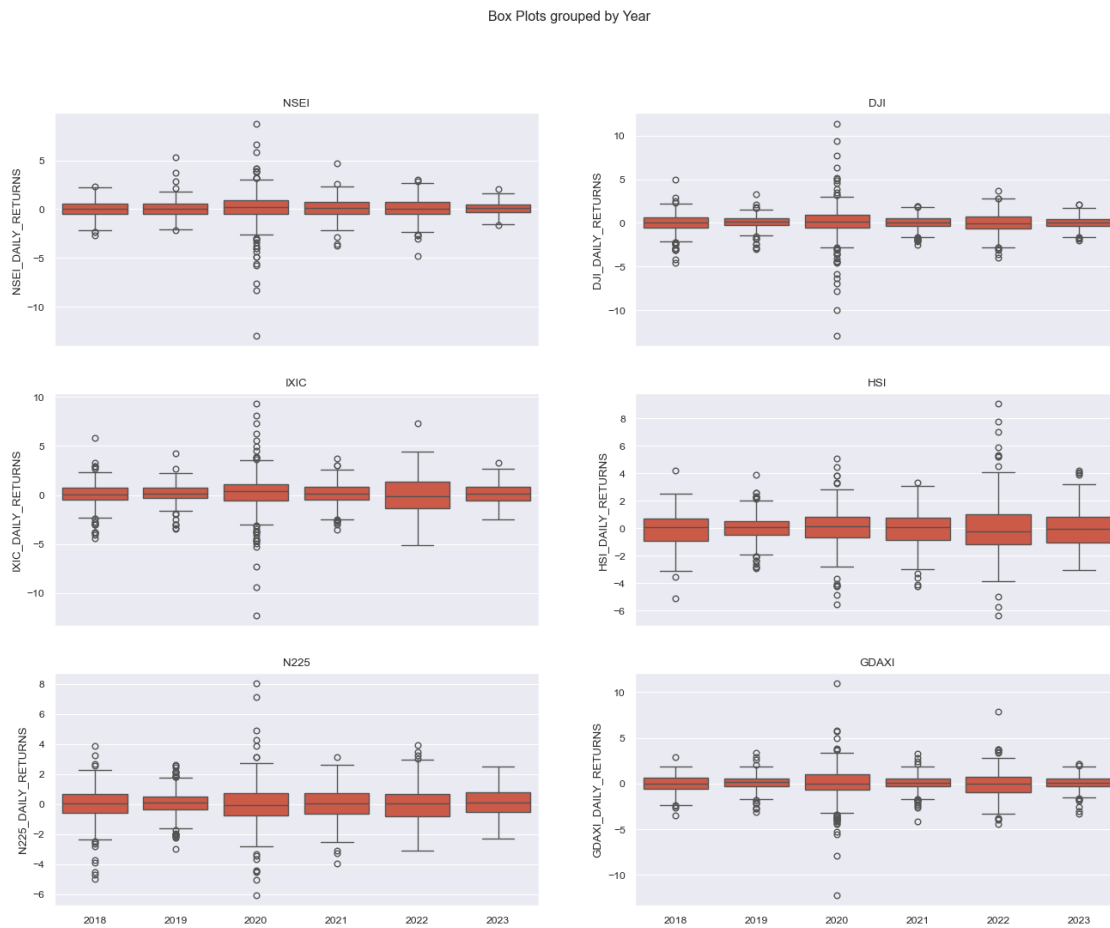
GDAXI

	count	mean	std	var
YEAR				
2018	260	-0.055542	0.975185	0.950985
2019	260	0.084212	0.887599	0.787832
2020	262	0.042611	2.063860	4.259519
2021	261	0.070506	0.898895	0.808012
2022	260	-0.034584	1.460441	2.132887
2023	260	0.082085	0.809460	0.655225

next, we...



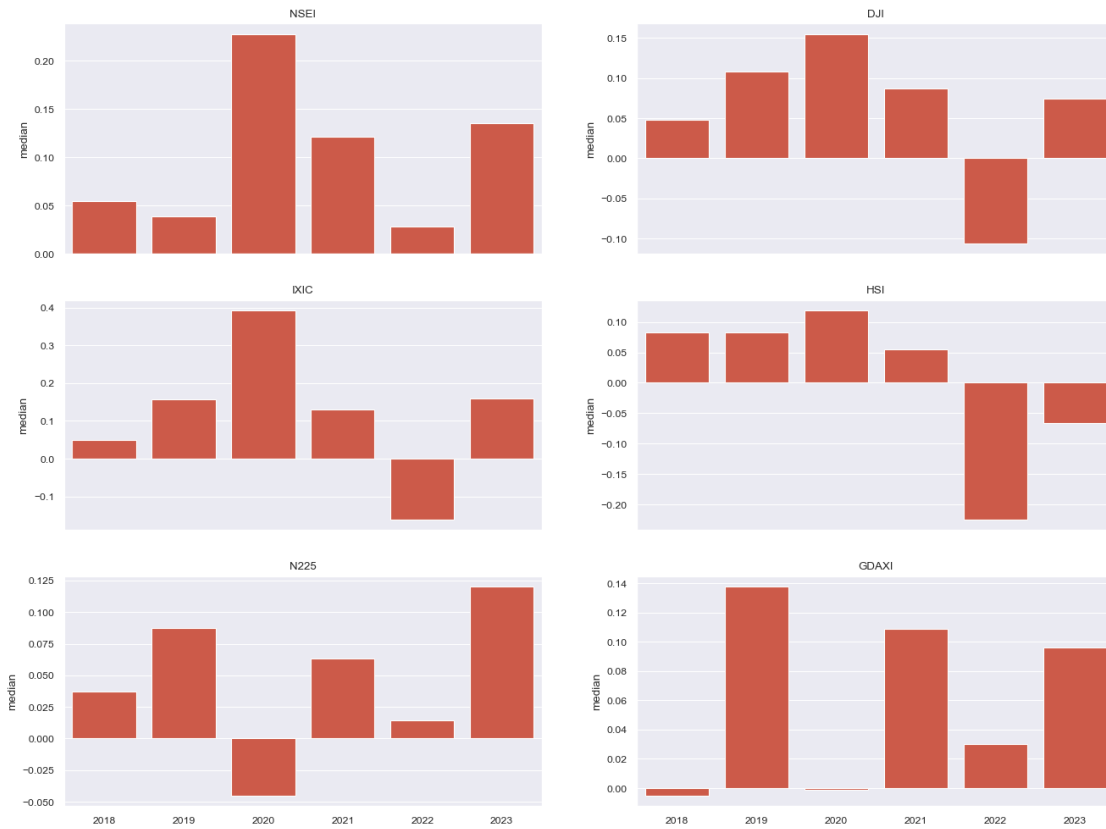
```
[ ]: performance_analytics_box_plots(master, "YEAR", "Box Plots grouped by Year")
```



next, we...

```
[ ]: performance_analytics_bar_plots(master, "YEAR", "Bar Plots of Median Returns_
    ↳grouped by Year")
```

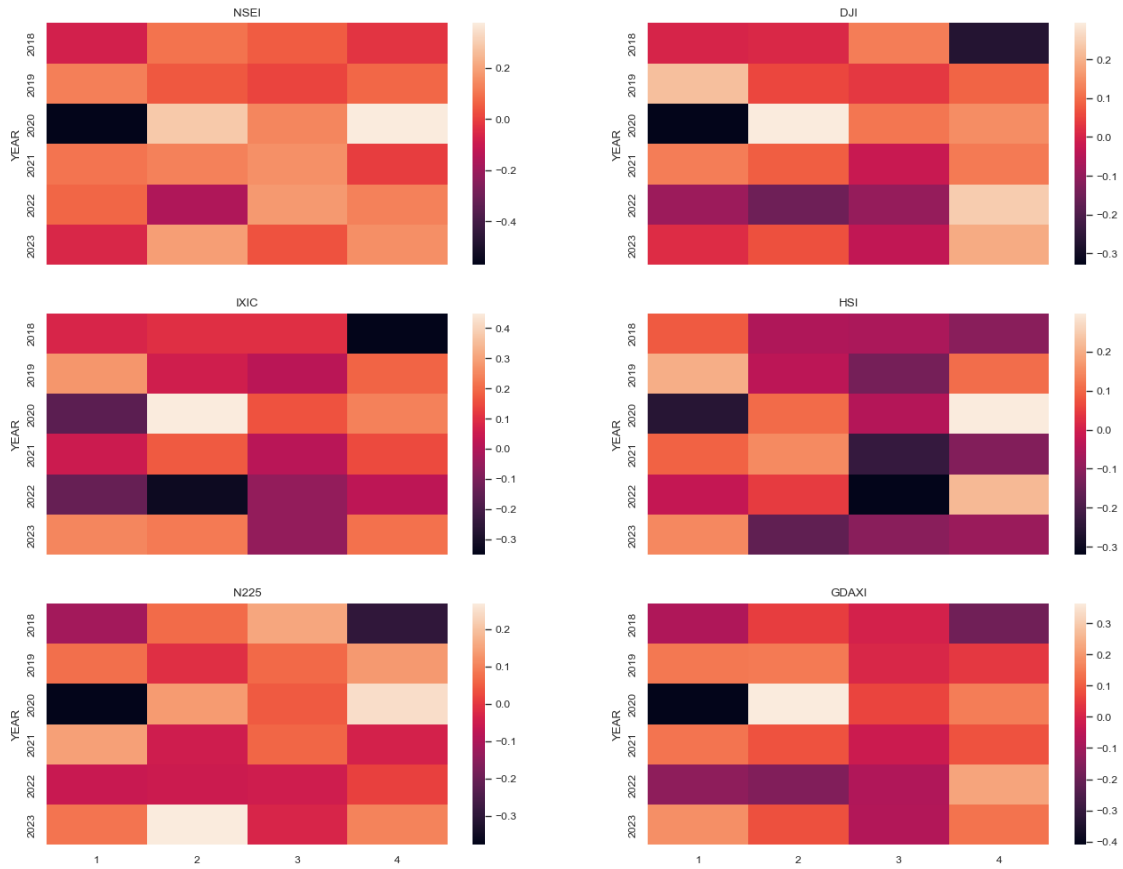
Bar Plots of Median Returns grouped by Year



next, we...

```
[ ]: performance_analytics_heat_maps(master, "YEAR", "Heat Maps of Mean Returns_
    ↳grouped by Year", aggfunc = "mean")
```

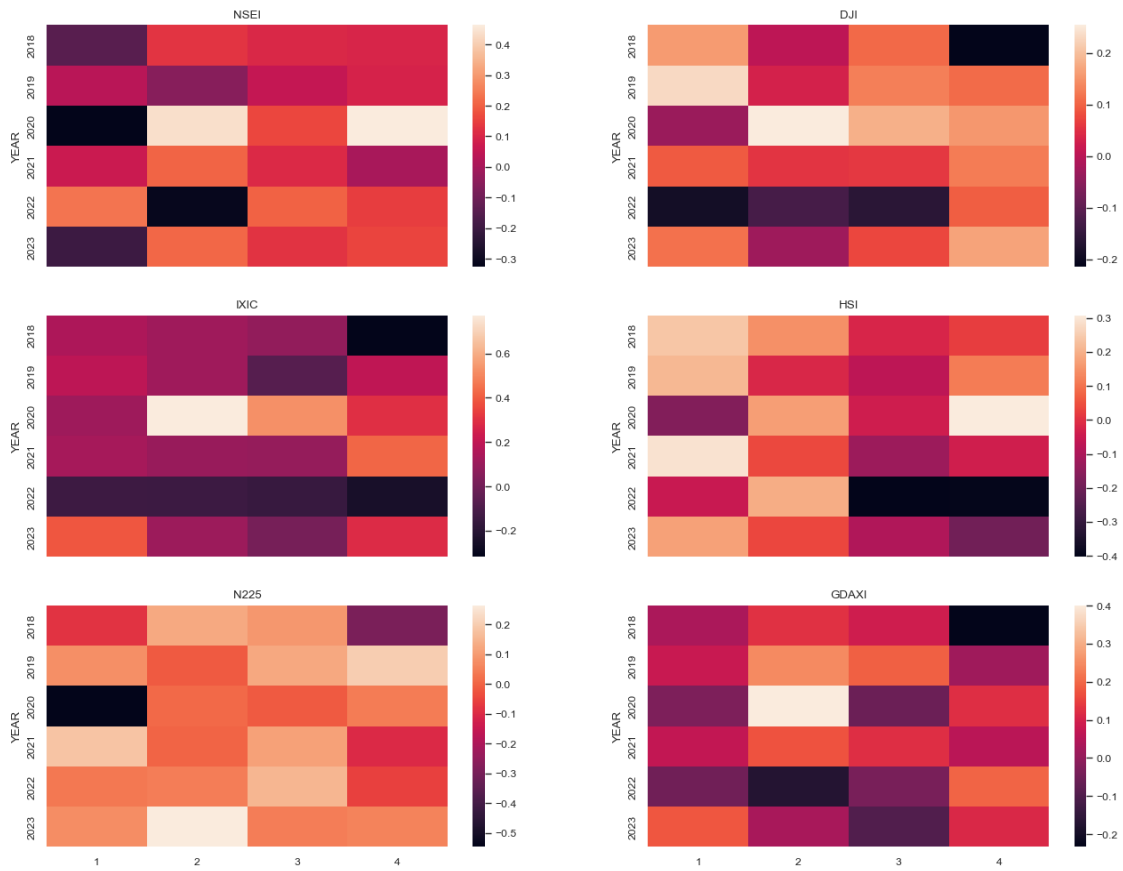
Heat Maps of Mean Returns grouped by Year



next, we...

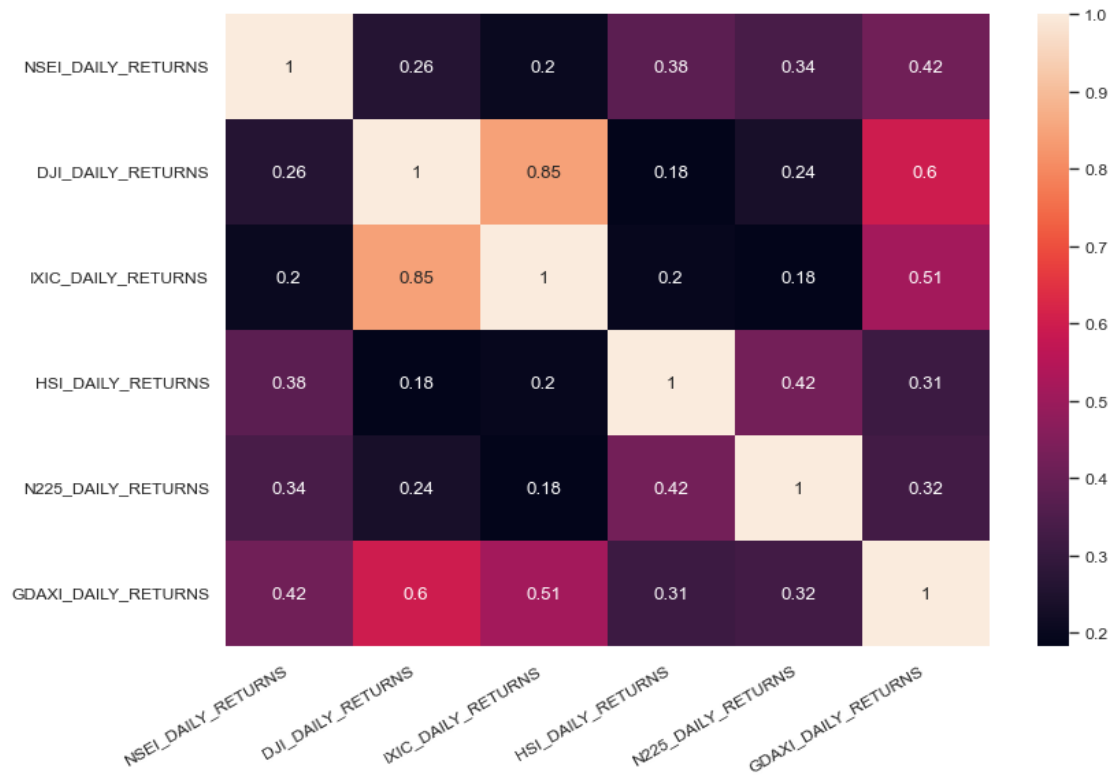
```
[ ]: performance_analytics_heat_maps(master, "YEAR", "Heat Maps of Median Returns_
    ↳grouped by Year")
```

Heat Maps of Median Returns grouped by Year



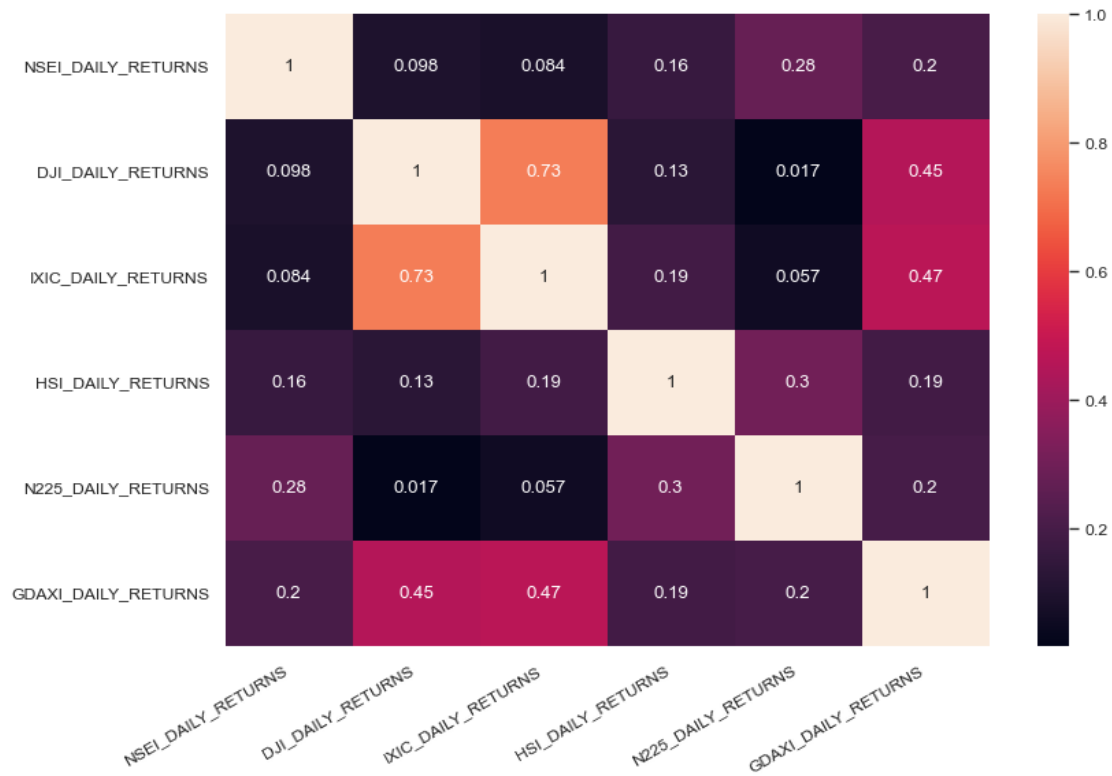
next, we...

```
[ ]: correlation_matrix(master)
```



next, we...

```
[ ]: correlation_matrix(master['2023-01-02':'2023-12-29'])
```



next, we...

```
[ ]: performance_analytics_tables(master, "PANDEMIC")
```

NSEI

	count	mean	std	var
PANDEMIC				
PRE_COVID	542	0.033358	0.830382	0.689535
COVID	589	0.068626	1.562565	2.441611
POST_COVID	432	0.082045	0.777193	0.604029

DJI

	count	mean	std	var
PANDEMIC				
PRE_COVID	542	0.033705	0.968612	0.938208
COVID	589	0.042948	1.656938	2.745443
POST_COVID	432	0.038478	0.980846	0.962060

IXIC

	count	mean	std	var
PANDEMIC				
PRE_COVID	542	0.061950	1.153434	1.330409
COVID	589	0.077150	1.812437	3.284927
POST_COVID	432	0.065371	1.525190	2.326205

HSI

	count	mean	std	var
PANDEMIC				
PRE_COVID	542	-0.012615	1.126131	1.268172
COVID	589	0.011764	1.507990	2.274035
POST_COVID	432	-0.046861	1.664055	2.769080

N225

	count	mean	std	var
PANDEMIC				
PRE_COVID	542	0.000132	1.046461	1.095080
COVID	589	0.016520	1.417410	2.009052
POST_COVID	432	0.054771	1.065944	1.136236

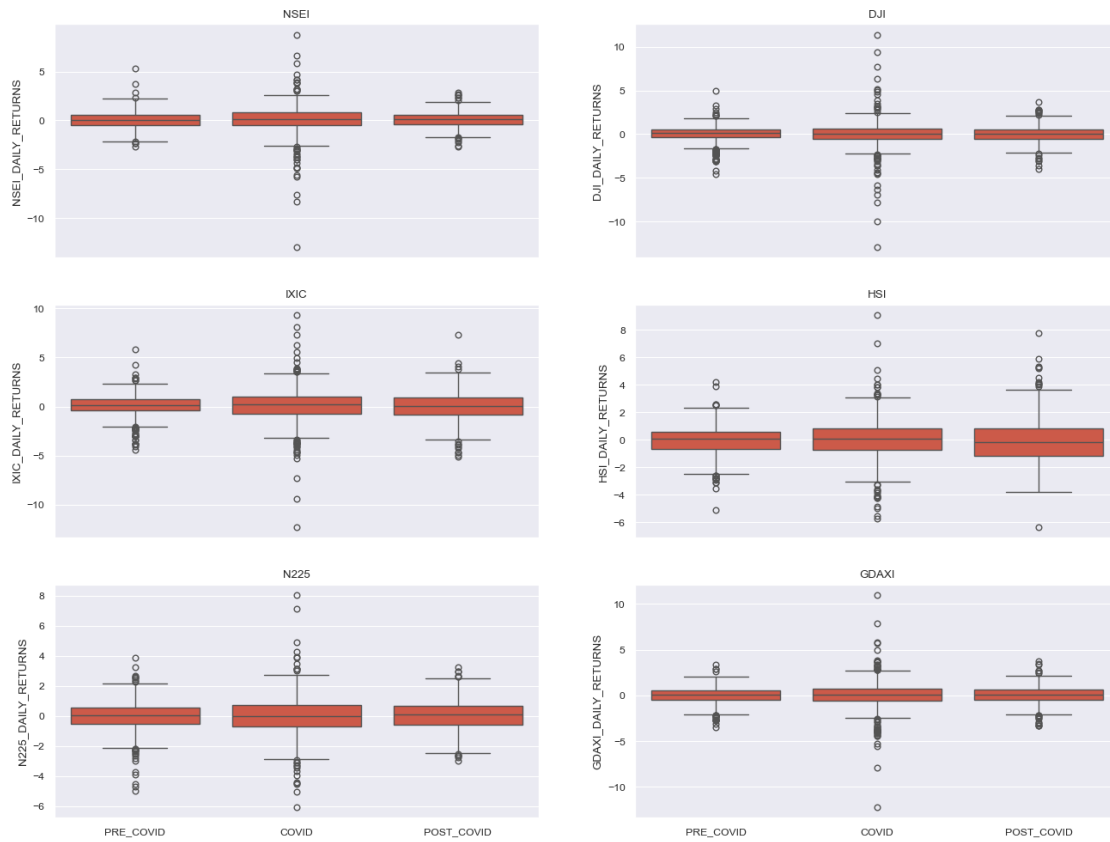
GDAXI

	count	mean	std	var
PANDEMIC				
PRE_COVID	542	0.011435	0.935235	0.874665
COVID	589	0.034896	1.634397	2.671252
POST_COVID	432	0.052360	1.027366	1.055480

next, we...

```
[ ]: performance_analytics_box_plots(master, "PANDEMIC", "Box Plots grouped by_\n↪Pandemic Period")
```

Box Plots grouped by Pandemic Period

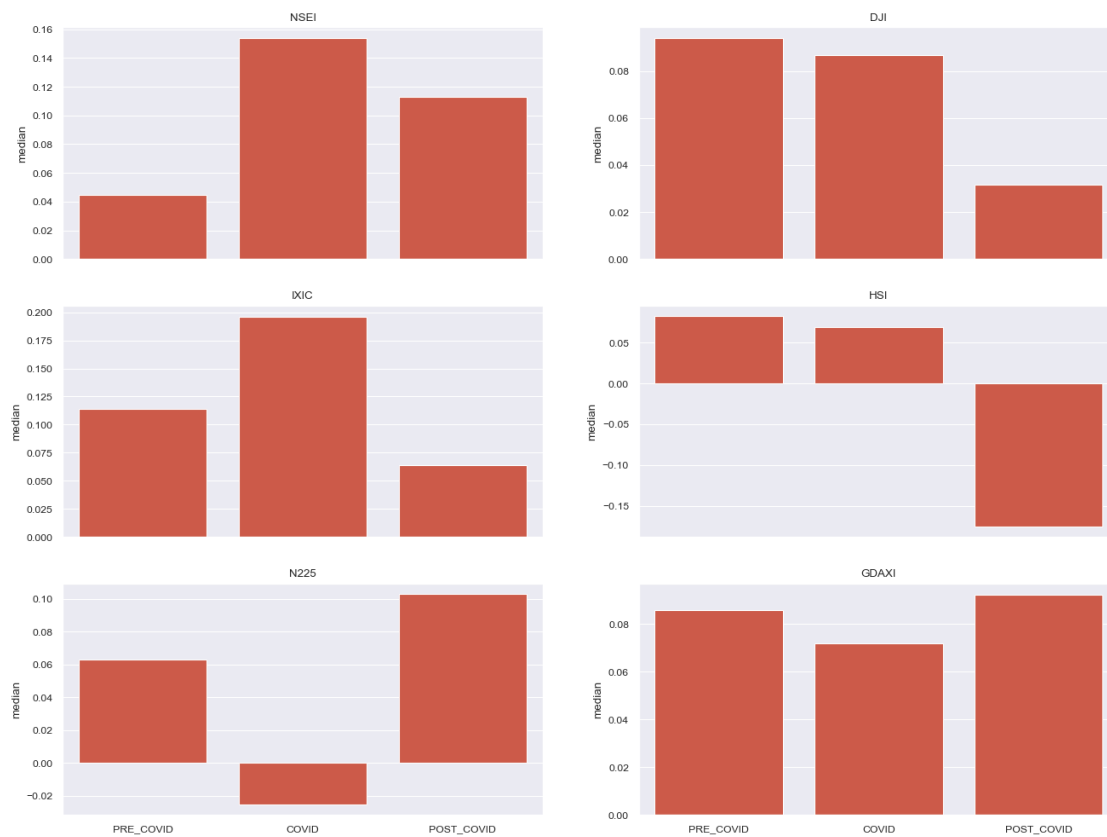


next, we...

```
[ ]: performance_analytics_bar_plots(master, "PANDEMIC", "Bar Plots grouped by_\n↪Pandemic Period")
```



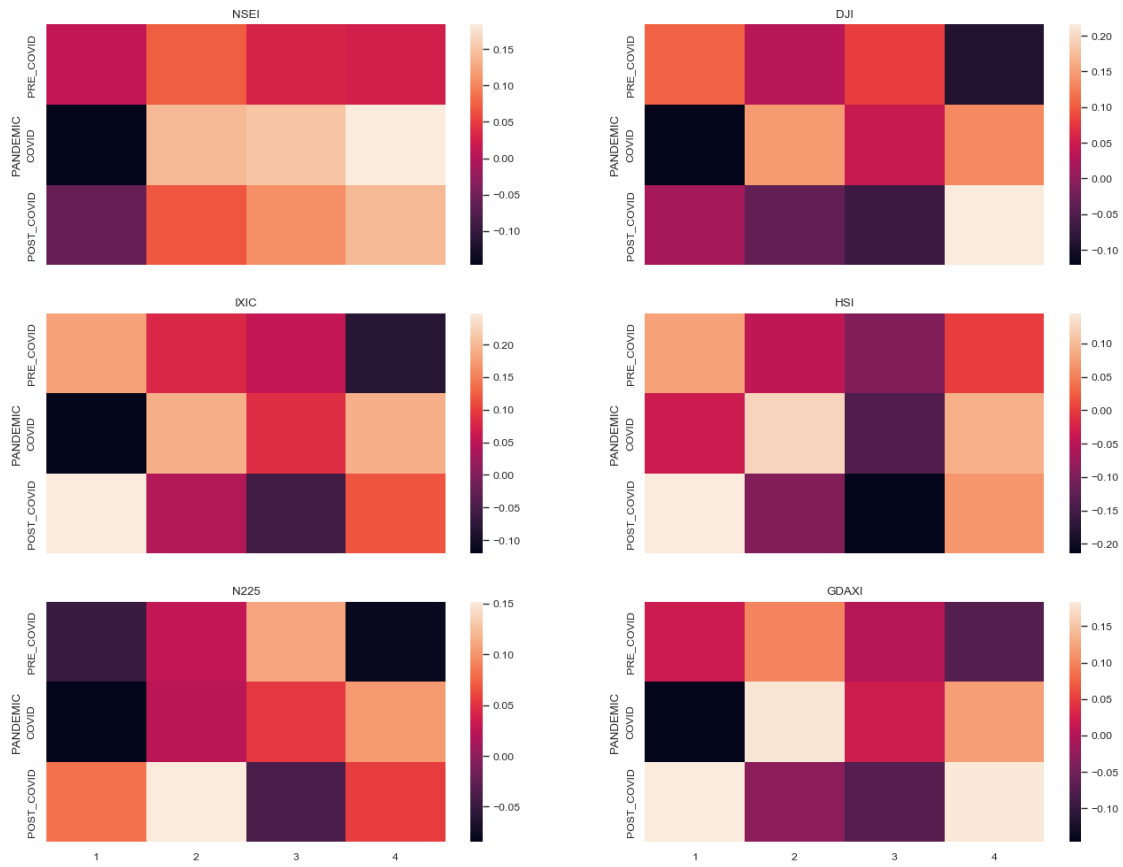
Bar Plots grouped by Pandemic Period



next, we...

```
[ ]: performance_analytics_heat_maps(master, "PANDEMIC", "Heat Maps of Mean Returns_
    ↳ grouped by Pandemic Period", aggfunc = "mean")
```

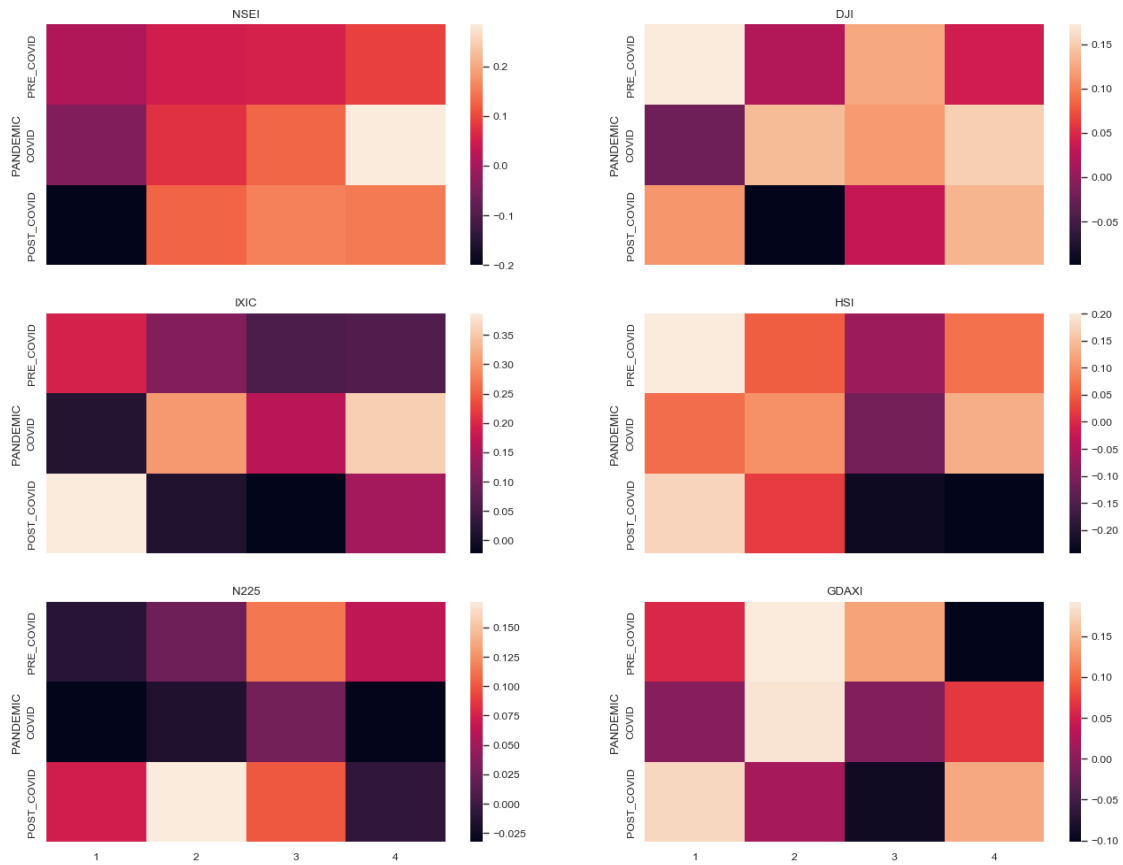
Heat Maps of Mean Returns grouped by Pandemic Period



next, we...

```
[ ]: performance_analytics_heat_maps(master, "PANDEMIC", "Heat Maps of Median_
↳Returns grouped by Pandemic Period")
```

Heat Maps of Median Returns grouped by Pandemic Period



next, we...

```
[ ]: for i in range(6):
    pre_covid = master.loc[(master['PANDEMIC'] == 'PRE_COVID'), [COLUMNS[i]]]
    post_covid = master.loc[(master['PANDEMIC'] == 'POST_COVID'), [COLUMNS[i]]]

    mean_pre = pre_covid.values.mean()
    post_count = np.where(post_covid[COLUMNS[i]].ge(mean_pre).values ==
↪True)[0][0]
    post_date = post_covid.index[post_covid[COLUMNS[i]].ge(mean_pre)][0].date()

    print(f"{INDICES[i].rjust(5)} returned to pre-covid levels (mean {mean_pre:
↪2.4f}) on {post_date} after {post_count} trading day(s)")
```

NSEI returned to pre-covid levels (mean 0.0334) on 2022-05-16 after 7 trading day(s)

DJI returned to pre-covid levels (mean 0.0337) on 2022-05-13 after 6 trading day(s)

IXIC returned to pre-covid levels (mean 0.0619) on 2022-05-10 after 3 trading day(s)

HSI returned to pre-covid levels (mean -0.0126) on 2022-05-11 after 4 trading day(s)

N225 returned to pre-covid levels (mean 0.0001) on 2022-05-06 after 1 trading day(s)

GDAXI returned to pre-covid levels (mean 0.0114) on 2022-05-10 after 3 trading day(s)

next, we...

```
[ ]: table1 = master.groupby("YEAR", observed = False)[["NSEI_OPEN_DIR"]].sum()
table2 = master.groupby("YEAR", observed = False)[["NSEI_OPEN_DIR"]].count()
table = ((table1["NSEI_OPEN_DIR"] / table2["NSEI_OPEN_DIR"]) * 100).round(2)

print("\nNifty Fifty Daily Movement\n")
print(f"\n{table}\n")
```

Nifty Fifty Daily Movement

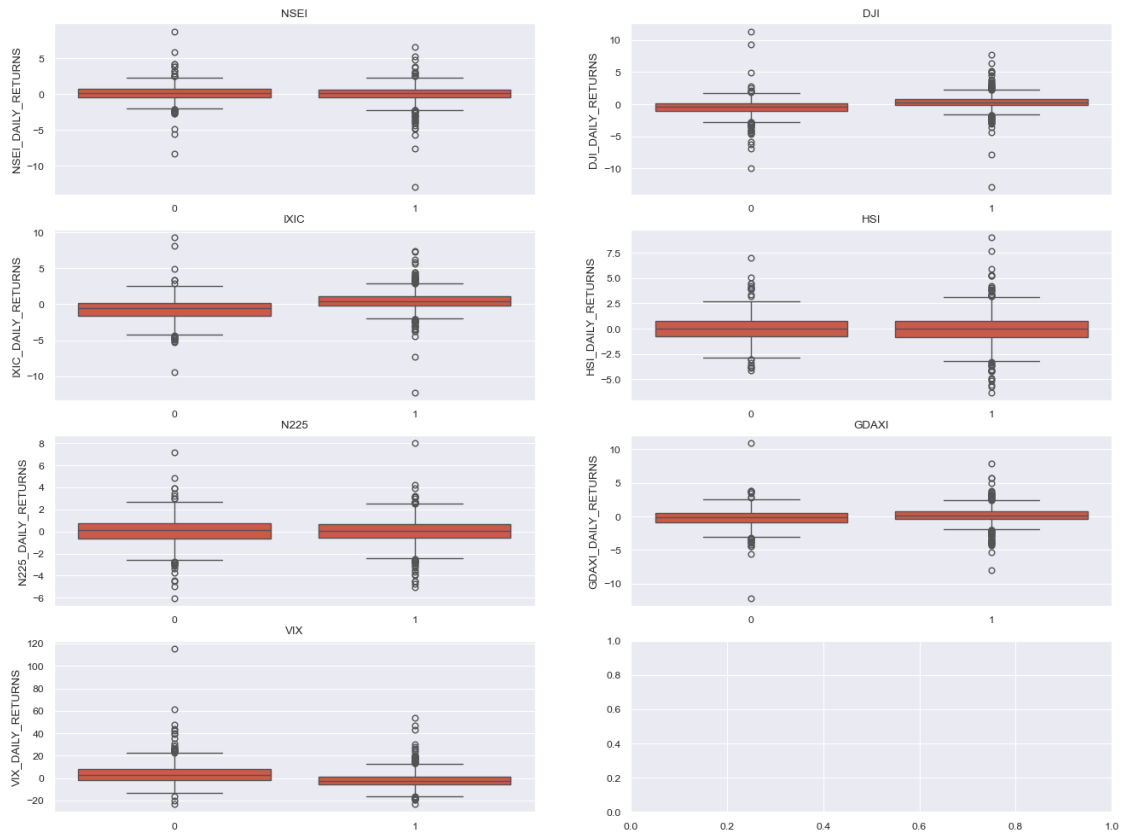
```
YEAR
2018    70.38
2019    69.23
2020    70.61
2021    71.65
2022    59.23
2023    67.31
Name: NSEI_OPEN_DIR, dtype: float64
```

next we...

```
[ ]: fig, axes = plt.subplots(4, 2, figsize = (16, 12))
fig.suptitle("Box Plots grouped by Open Direction")

for index in range(7):
    axes[index // 2, index % 2].set_title(INDICES[index])
    sns.boxplot(x = master["NSEI_OPEN_DIR"], y = master[COLUMNS[index]].
    ↪shift(), ax = axes[index // 2, index % 2])
    axes[index // 2, index % 2].set_xlabel("")
```

### Box Plots grouped by Open Direction



next, we...

```
[ ]: RATIOS      = ["NSEI_HL_RATIO", "DJI_HL_RATIO"]
      INDICATORS = ["NSEI_RSI", "DJI_RSI", "NSEI_TSI", "DJI_TSI"]
      ALL_COLS   = COLUMNS + RATIOS + INDICATORS
```

next, we...

```
[ ]: master["NSEI_HL_RATIO"] = master["NSEI_HIGH"] / master["NSEI_LOW"]
master["DJI_HL_RATIO"] = master["DJI_HIGH"] / master["DJI_LOW"]
```

next, we...

```
[ ]: master["NSEI_RSI"] = ta.momentum.rsi(master["NSEI_CLOSE"])
master["DJI_RSI"] = ta.momentum.rsi(master["DJI_CLOSE"])

master["NSEI_TSI"] = ta.momentum.tsi(master["NSEI_CLOSE"])
master["DJI_TSI"] = ta.momentum.tsi(master["DJI_CLOSE"])
```

next, we...

```
[ ]: data = pd.concat([master["NSEI_OPEN_DIR"].shift(-1), master[ALL_COLS]], axis = 1)
data.dropna(inplace = True)
data.head()
```

```
[ ]:      NSEI_OPEN_DIR  NSEI_DAILY_RETURNS  DJI_DAILY_RETURNS  \
Date
2018-02-22          1.0          -0.141862          0.664177
2018-02-23          1.0          1.043559          1.392128
2018-02-26          1.0          0.872647          1.577556
2018-02-27          0.0          -0.267418          -1.163939
2018-02-28          0.0          -0.582229          -1.498739
```

```
      IXIC_DAILY_RETURNS  HSI_DAILY_RETURNS  N225_DAILY_RETURNS  \
Date
2018-02-22          -0.112772          -1.483242          -1.066738
2018-02-23          1.765585          0.973627          0.719252
2018-02-26          1.145773          0.740168          1.191496
2018-02-27          -1.227654          -0.729999          1.066320
2018-02-28          -0.782232          -1.355797          -1.436450
```

```
      GDAXI_DAILY_RETURNS  VIX_DAILY_RETURNS  NSEI_HL_RATIO  \
Date
2018-02-22          -0.068803          -6.493512          1.005502
2018-02-23          0.175574          -11.912391          1.009854
2018-02-26          0.346449          -4.184352          1.006915
2018-02-27          -0.289850          17.658227          1.008959
2018-02-28          -0.439373          6.777839          1.007069
```

```
      DJI_HL_RATIO  NSEI_RSI  DJI_RSI  NSEI_TSI  DJI_TSI
Date
2018-02-22      1.012146  35.462139  46.645122 -30.229045 -9.335285
2018-02-23      1.011394  43.991068  52.167111 -27.688141 -7.175461
2018-02-26      1.013160  50.003304  57.597238 -23.576140 -3.663260
2018-02-27      1.015449  48.278103  52.762870 -20.700940 -2.074670
2018-02-28      1.022129  44.673823  47.319430 -19.286991 -2.368269
```

next, we...

```
[ ]: X = data[ALL_COLS]
y = data['NSEI_OPEN_DIR']
```

next, we...

```
[ ]: X.insert(loc = 0, column = "Intercept", value = 1)
```

next, we...

```
[ ]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,
↳ random_state = 1337)
```

next, we...

```
[ ]: def prune(X, y, verbose = True):
    dropped = []
    while True:
        model = Logit(y, X).fit(dispatch = 0)

        insignificant = [p for p in zip(model.pvalues.index[1:], model.
↳ pvalues[1:]) if p[1] > 0.05]

        values = [variance_inflation_factor(model.model.exog, i) for i in
↳ range(1, model.model.exog.shape[1])]
        colinear = [val for val in zip(model.model.exog_names[1:], values) if
↳ val[1] > 5]

        if insignificant:
            insignificant.sort(key = lambda p: -p[1])

            if verbose:
                print(f"dropping {insignificant[0][0]} with p-value
↳ {insignificant[0][1]}")

            X = X.drop([insignificant[0][0]], axis = 1)
            dropped.append(insignificant[0][0])

        elif colinear:
            colinear.sort(key = lambda c: -c[1])

            if verbose:
                print(f"dropping {colinear[0][0]} with vif {colinear[0][1]}")

            X = X.drop([colinear[0][0]], axis = 1)
            dropped.append(colinear[0][0])

        else:
            return model, dropped
```

next, we...

```
[ ]: model, dropped = prune(X_train, y_train)
```

```
dropping DJI_DAILY_RETURNS with p-value 0.7234766099769976
dropping GDAXI_DAILY_RETURNS with p-value 0.6162105670377191
dropping NSEI_HL_RATIO with p-value 0.42776185052464266
dropping DJI_HL_RATIO with p-value 0.15630559889450327
```

dropping NSEI\_DAILY\_RETURNS with p-value 0.13281329048460586  
dropping NSEI\_TSI with vif 5.865700460659149  
dropping NSEI\_RSI with p-value 0.7783762272652992

next, we...

```
[ ]: model.summary()
```

```
[ ]:
```

<b>Dep. Variable:</b>	NSEI_OPEN_DIR	<b>No. Observations:</b>	1220
<b>Model:</b>	Logit	<b>Df Residuals:</b>	1213
<b>Method:</b>	MLE	<b>Df Model:</b>	6
<b>Date:</b>	Tue, 25 Jun 2024	<b>Pseudo R-squ.:</b>	0.1375
<b>Time:</b>	20:24:32	<b>Log-Likelihood:</b>	-660.02
<b>converged:</b>	True	<b>LL-Null:</b>	-765.23
<b>Covariance Type:</b>	nonrobust	<b>LLR p-value:</b>	1.141e-42

	coef	std err	z	P >  z	[0.025	0.975]
Intercept	-1.4041	0.656	-2.139	0.032	-2.690	-0.118
IXIC_DAILY_RETURNS	0.4552	0.075	6.093	0.000	0.309	0.602
HSI_DAILY_RETURNS	-0.1395	0.053	-2.632	0.008	-0.243	-0.036
N225_DAILY_RETURNS	-0.1960	0.068	-2.897	0.004	-0.329	-0.063
VIX_DAILY_RETURNS	-0.0397	0.013	-3.054	0.002	-0.065	-0.014
DJI_RSI	0.0447	0.013	3.415	0.001	0.019	0.070
DJI_TSI	-0.0205	0.008	-2.660	0.008	-0.036	-0.005

next, we...

```
[ ]: vif_data = pd.DataFrame()
vif_data["Feature"] = model.model.exog_names[1:]
vif_data["VIF"] = [variance_inflation_factor(model.model.exog, i) for i in
range(1, model.model.exog.shape[1])]
vif_data
```

```
[ ]:
```

	Feature	VIF
0	IXIC_DAILY_RETURNS	2.073867
1	HSI_DAILY_RETURNS	1.244922
2	N225_DAILY_RETURNS	1.353286
3	VIX_DAILY_RETURNS	1.994009
4	DJI_RSI	4.850250
5	DJI_TSI	4.379409

next, we...

```
[ ]: y_pred = model.predict(X_train.drop(dropped, axis = 1))
fpr, tpr, thresholds = roc_curve(y_train, y_pred)

plt.figure(figsize = (16, 12))

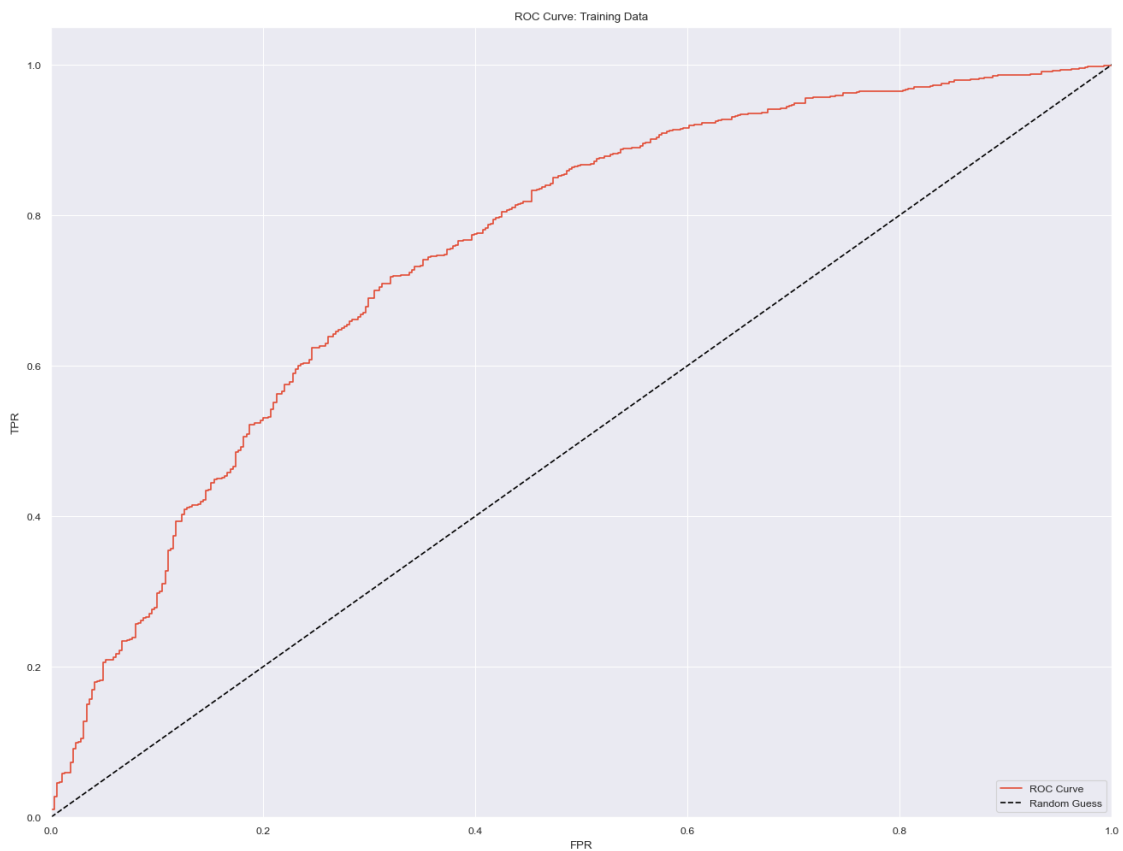
plt.plot(fpr, tpr, label = 'ROC Curve')
plt.plot([0, 1], [0, 1], 'k--', label = 'Random Guess')
```



```
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])

plt.title(f"ROC Curve: Training Data")
plt.xlabel('FPR')
plt.ylabel('TPR')

plt.legend(loc = 'lower right')
plt.show()
```



next, we...

```
[ ]: optimal_threshold = round(thresholds[np.argmax(tpr - fpr)], 3)
print(f'Best Threshold: {optimal_threshold}')
```

Best Threshold: 0.684

next, we...

```
[ ]: auc_roc = roc_auc_score(y_train, y_pred)
print(f'AUC ROC: {auc_roc}')
```

AUC ROC: 0.7529115595469844

next, we...

```
[ ]: y_pred_class = np.where(y_pred <= optimal_threshold, 0, 1)
print(classification_report(y_train, y_pred_class))
```

	precision	recall	f1-score	support
0.0	0.53	0.68	0.60	391
1.0	0.83	0.72	0.77	829
accuracy			0.70	1220
macro avg	0.68	0.70	0.68	1220
weighted avg	0.73	0.70	0.71	1220

next, we...

```
[ ]: table = pd.crosstab(y_pred_class, y_train)
print(table)
```

	0.0	1.0
row_0		
0	265	234
1	126	595

next, we...

```
[ ]: sensitivity = round((table.iloc[1, 1] / (table.iloc[0, 1] + table.iloc[1, 1]))
    ↳ * 100, 2)
specificity = round((table.iloc[0, 0] / (table.iloc[0, 0] + table.iloc[1, 0]))
    ↳ * 100, 2)

print(f"Sensitivity: {sensitivity}%")
print(f"Specificity: {specificity}%")
```

Sensitivity: 71.77%

Specificity: 67.77%

next, we...

```
[ ]: y_test_pred = model.predict(X_test.drop(dropped, axis = 1))

fpr, tpr, thresholds = roc_curve(y_test, y_test_pred)

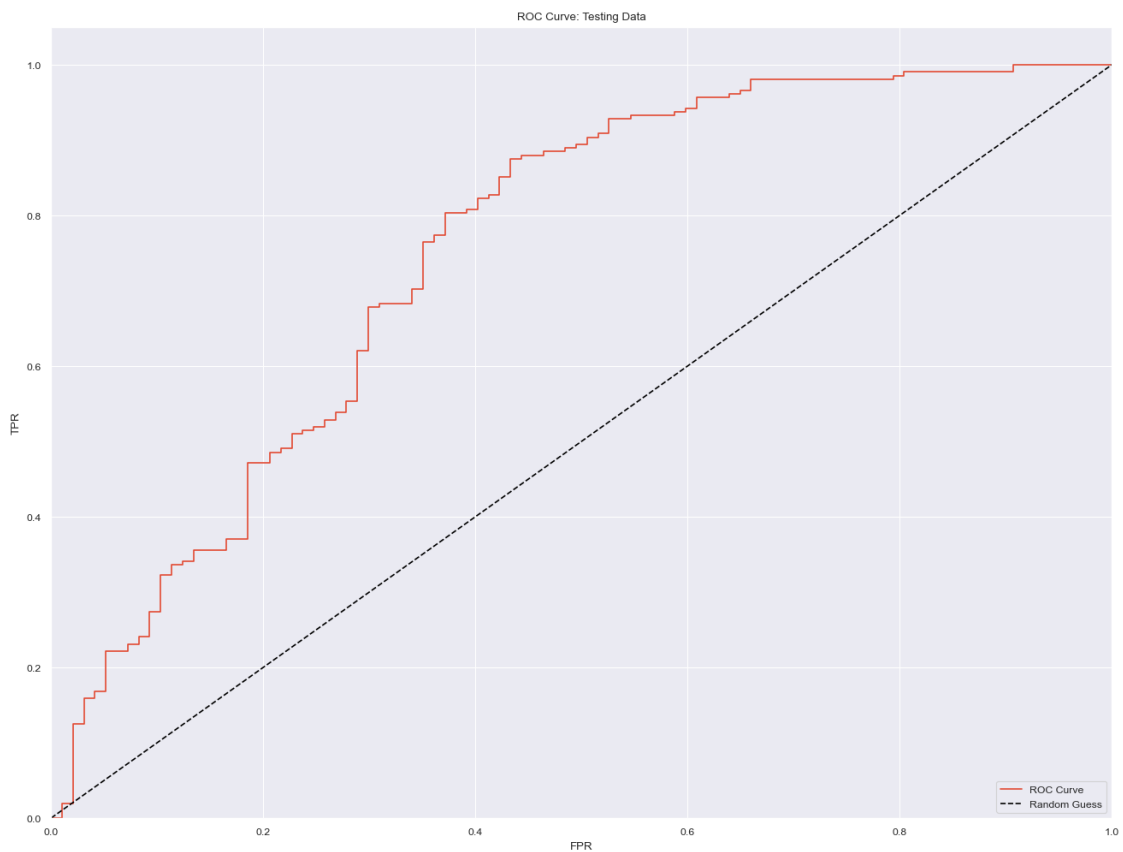
plt.figure(figsize = (16, 12))
```

```
plt.plot(fpr, tpr, label = 'ROC Curve')
plt.plot([0, 1], [0, 1], 'k--', label = 'Random Guess')

plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])

plt.title(f"ROC Curve: Testing Data")
plt.xlabel('FPR')
plt.ylabel('TPR')

plt.legend(loc = 'lower right')
plt.show()
```



next, we...

```
[ ]: auc_roc = roc_auc_score(y_test, y_test_pred)
print(f'AUC ROC: {auc_roc}')
```

AUC ROC: 0.7520816812053925

next, we...

```
[ ]: y_test_pred_class = np.where(y_test_pred <= optimal_threshold, 0, 1)
      print(classification_report(y_test, y_test_pred_class))
```

	precision	recall	f1-score	support
0.0	0.53	0.65	0.58	97
1.0	0.82	0.73	0.77	208
accuracy			0.70	305
macro avg	0.67	0.69	0.67	305
weighted avg	0.72	0.70	0.71	305

next, we...

```
[ ]: table = pd.crosstab(y_test_pred_class, y_test)
      print(table)
```

NSEI_OPEN_DIR	0.0	1.0
row_0		
0	63	57
1	34	151

next, we...

```
[ ]: sensitivity = round((table.iloc[1, 1] / (table.iloc[0, 1] + table.iloc[1, 1]))
      ↪ * 100, 2)
      specificity = round((table.iloc[0, 0] / (table.iloc[0, 0] + table.iloc[1, 0]))
      ↪ * 100, 2)

      print(f"Sensitivity: {sensitivity}%")
      print(f"Specificity: {specificity}%")
```

Sensitivity: 72.6%  
Specificity: 64.95%