Global Stock Market Analytics

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Introduction

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 five parts:

1. preparing the master data from the global indices
2. preliminary analysis of the data
3. predictive modelling of open direction of Nifty 50
4. comparing different models at predicting open direction
5. sentiment analysis of X / Twitter data relating to Nifty 50

Phase 1 - Prepare the Master Data

The indexes of interest are:

- NSEI: Nifty 50
- DJI: Dow Jones Index
- IXIC: Nasdaq
- HSI: Hang Seng
- N225: Nikkei 225
- GDAXI: Dax
- VIX: Volatility Index

Phase 1 - Prepare the Master Data

We download and merge the required data, using LOCF to impute missing data, and adding variables for MONTH, QUARTER, and YEAR.

```
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

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

# 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
```

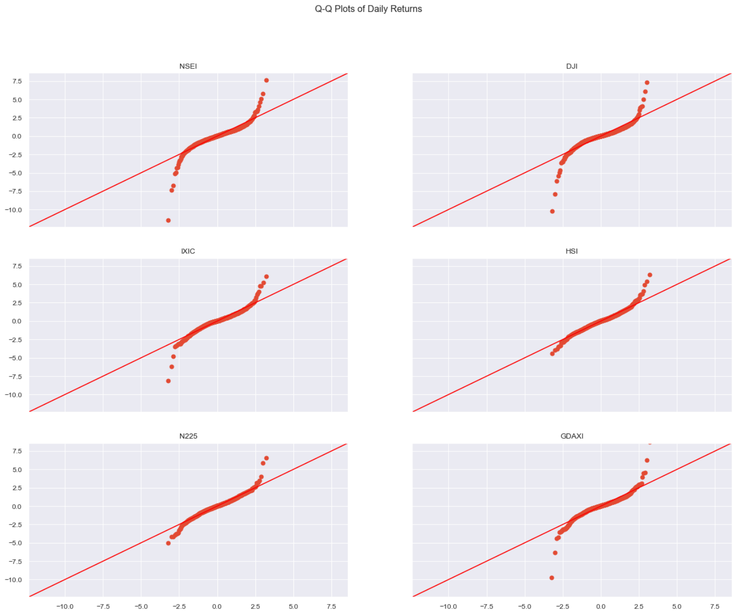
Phase 2 - Preliminary Analysis

We perform some preliminary analysis on the master data hoping to answer the following questions:

1. Which index has given consistently good returns?
2. Which index was highly volatile?
3. How are global markets correlated during 6 years period and is the correlation structure similar in the most recent year - i.e. 2023?
4. Assuming a primary target variable of "Nifty Opening Price Direction", what are preliminary insights?

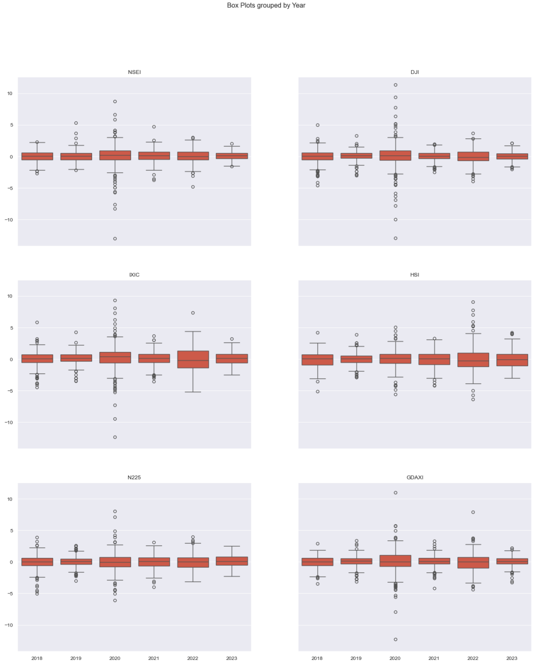
Phase 2 - Preliminary Analysis

Looking at the Q-Q Plots, the daily returns do not appear to follow - or be drawn from - a Normal Distribution - specifically at the tails. But normality is not a requisite or assumption of Logistic Regression with respect to independent variables.



Phase 2 - Which index has given consistently good returns?

All indexes seem pretty consistent - all years have similar spreads, and consistent medians, with one or two exceptions. All indexes for 2020 have more outliers than normal. But HSI seems to have more outliers in 2022 than in 2020.



Phase 2 - Which index has given consistently good returns?

Looking at the summary statistics, the clear winner here is NSEI - not one year in the range has a negative mean return. And with the exception of 2020 and 2022, NSEI has low volatility (< 1) throughout all years.

NSEI

YEAR	count	mean	std	var
2018	260	0.012	0.804	0.647
2019	260	0.062	0.862	0.744
2020	262	0.059	2.004	4.015
2021	261	0.094	0.980	0.960
2022	260	0.055	1.096	1.202
2023	260	0.079	0.620	0.384

Phase 2 - Which index was highly volatile?

As for the most volatile indexes, it's a toss between IXIC and HSI, both of whom have high volatility (> 1) when compared to the other indexes.

IXIC

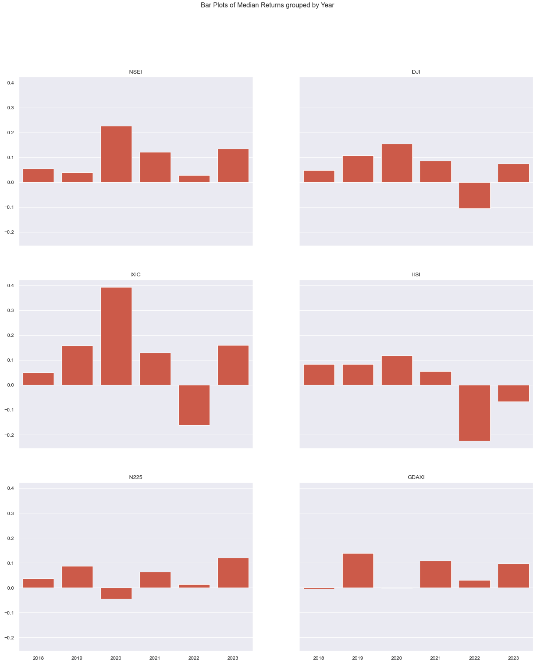
YEAR	count	mean	std	var
2018	260	-0.020	1.330	1.768
2019	260	0.133	0.975	0.950
2020	262	0.170	2.200	4.838
2021	261	0.096	1.124	1.262
2022	260	-0.124	2.000	4.001
2023	260	0.157	1.085	1.177

HSI

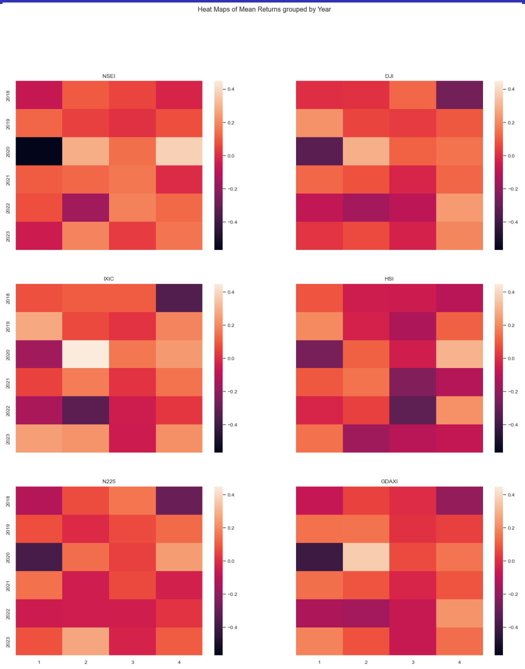
YEAR	count	mean	std	var
2018	260	-0.035	1.244	1.547
2019	260	0.033	0.981	0.962
2020	262	0.026	1.445	2.087
2021	261	-0.028	1.262	1.593
2022	260	-0.021	2.054	4.221
2023	260	-0.053	1.409	1.984

Phase 2 - Which index has given consistently good returns?

Looking at bar plots for median returns by year, again the clear winner here is NSEI - at no time is the median daily returns for any of the years below 0. IXIC has an unusually high 2020, but a bad 2022. HSI also has an unusually bad 2022.



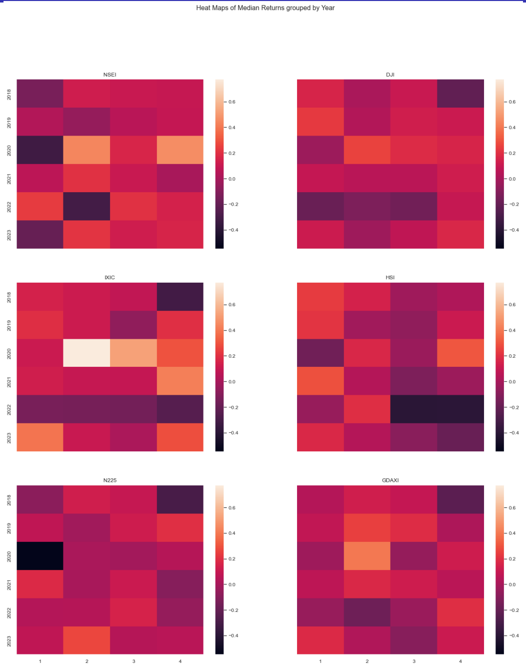
Phase 2 - Which index has given consistently good returns?



Looking at heat maps of mean returns, with the exception of the 1st quarter in 2020, NSEI has pretty consistent daily returns - where most cells sre pretty bright, denoting above 0. Most of the other indexes have a blend of light and dark, which would indicate more volatile behaviour over the quarters.

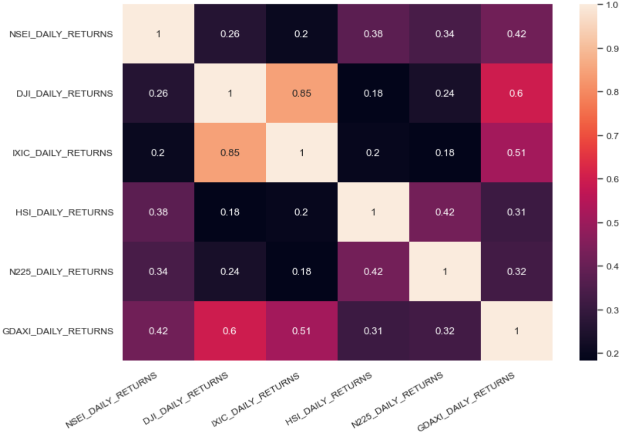
Phase 2 - Which index has given consistently good returns?

On the other hand, when looking at median returns across quarters NSEI seems pretty average - there does not seem to be a clear winner here.



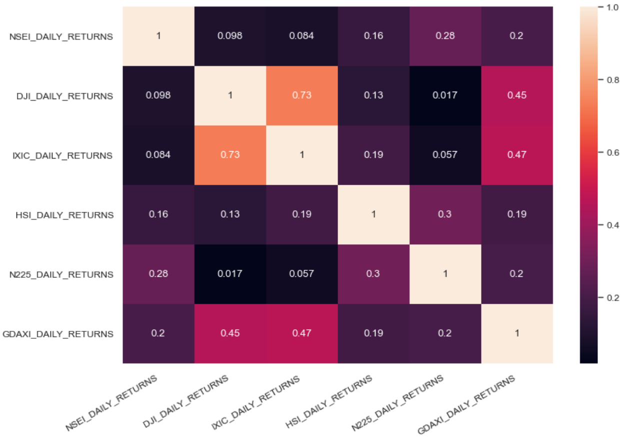
Phase 2 - How are global markets correlated during the 6 years period?

It looks like strong correlation between daily returns of IXIC and DJI, and some correlation between GDAXI and DJI. These indexes are likely to result in multicolinearity at the regression stage.



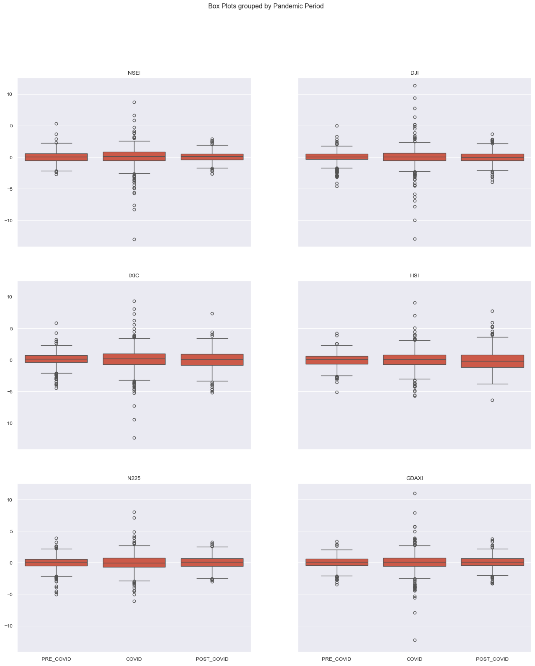
Phase 2 - Is the correlation structure similar in the recent year - 2023?

We can see similar - but slightly weaker - correlations exist between the same indexes for 2023.



Phase 2 - Covid Period

We can see that the spreads of each index over the Pandemic are consistent, with the Covid period itself having more outliers - which of course you might expect.



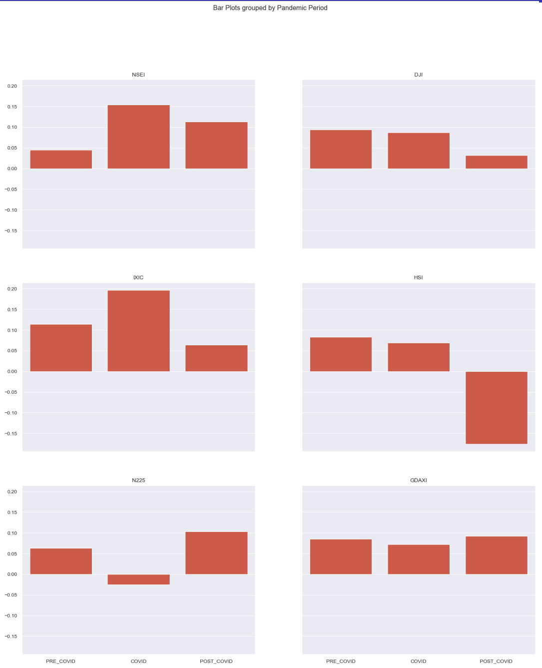
Phase 2 - Covid Period

All indexes had higher volatility over the Covid period.

- NSEI performed reasonably well over the Covid period, with an increase in volatility in the period, and with a significant bump in the Post Covid period.
- DJI seemed consistent over the three periods, with an increase in volatility in the Covid period.
- IXIC looked pretty good over the three period, but maybe slightly more volatile overall, and in particular in the Covid period.
- HSI has performed poorely in general, with negative returns in the pre and post Covid periods, and with consistently greater volatility than most.
- N225 appears to perform not so well, and with relatively high volatility.
- GDAXI also appears to perform not so well in general, and with relatively high volatility.

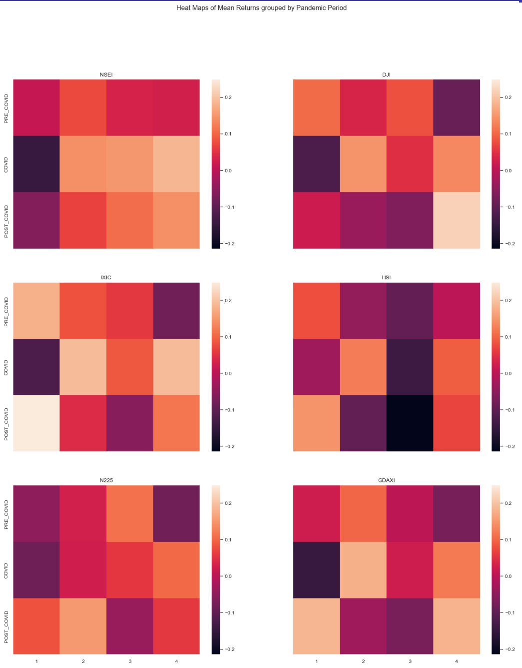
Phase 2 - Covid Period

With respect to returns, we can see that IXIC looks like the clear winner, with NSEI in second place, and DJI and GSAXI in a fight for third place. HSI appears to have had a terrible Post Covid period, and N225 appears to have had a pretty bad Covid period.



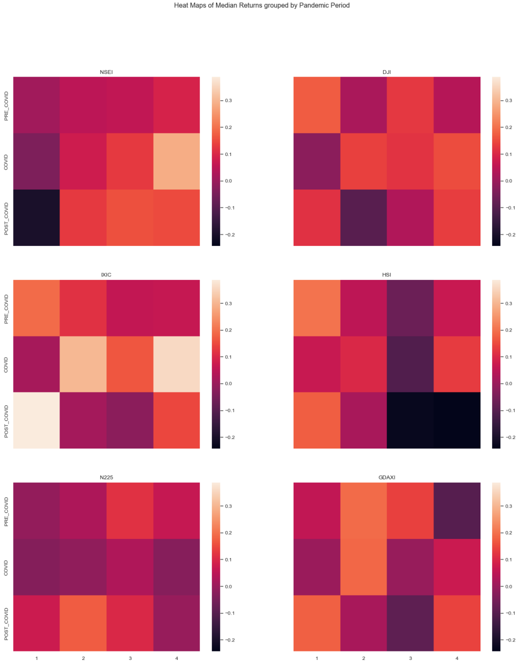
Phase 2 - Covid Period

Again, NSEI appears to be the most consistent of all indexes. All indexes have bad first quarters during the Pandemic, but improve post Covid.



Phase 2 - Covid Period

Median returns tells a similar story over the Pandemic period - HSI in particular appears to have had the worst recovery.



Phase 2 - Covid Period

We try to estimate the time taken for each of the indexes to return to the Pre Covid levels - the approach is to find how many days it takes for each index to reach a value greater than or equal to the Pre Covid mean returns value.

```
 NSEI returned to pre-covid levels on 2022-05-16 after 7 trading day(s)
  DJI returned to pre-covid levels on 2022-05-13 after 6 trading day(s)
 IXIC returned to pre-covid levels on 2022-05-10 after 3 trading day(s)
  HSI returned to pre-covid levels on 2022-05-11 after 4 trading day(s)
 N225 returned to pre-covid levels on 2022-05-06 after 1 trading day(s)
GDAXI returned to pre-covid levels on 2022-05-10 after 3 trading day(s)
```

Interestingly, N225 returned to it's Pre Covid level after just 1 day.

Phase 2 - Nifty Opening Price Direction: Preliminary Insights?

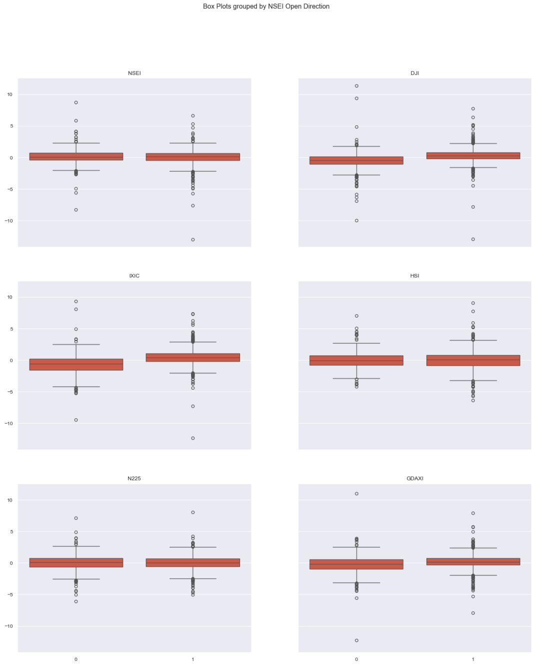
We define the Nifty Opening Price Direction - NSEI_OPEN_DIR - as 1 if the value of the NSEI Opening price at time t is greater than the value of the NSEI Closing price at time $t-1$, and 0 otherwise. Lets look at the percentages of NSEI_OPEN_DIR $= 1$ by year:

```
Nifty Fifty Daily Movement

YEAR
2018     70.38%
2019     69.23%
2020     70.61%
2021     71.65%
2022     59.23%
2023     67.31%
```

With the exception of 2022, every year has between 67% and 72% where NSEI_OPEN_DIR $=$ 1.

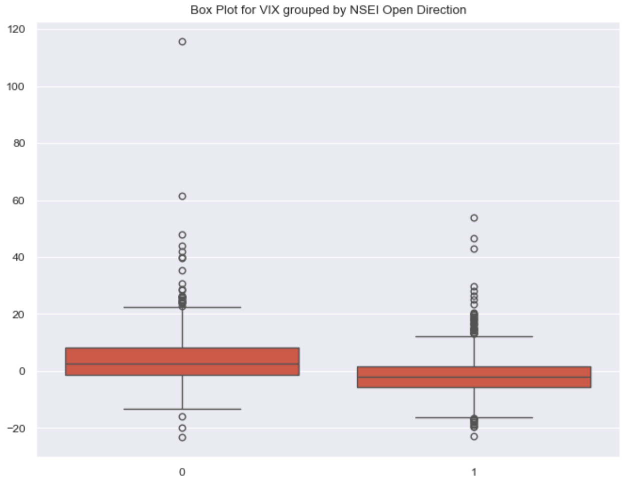
Phase 2 - Nifty Opening Price Direction

Looking at the the box plots, the data looks fairly consistent across each category of NSEI_OPEN_DIR, with the exceptions of DJI, IXIC and VIX.



Phase 2 - Nifty Opening Price Direction

We look at VIX separately - as it requires a different scale.



Phase 3 - Logistic Model

Before proceeding with modelling NSEI_OPEN_DIR, lets define, and add, some ratios and indicators, making use of the Python technical analysis library:

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

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"])
```

Phase 3 - Logistic Model

We define a function that will prune any features that are either found to be insignificant, or that are found to be collinear:

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

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

        values   = [variance_inflation_factor(exog, i) for i in range(1, exog.shape[1])]
        colinear = [val for val in zip(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


model, dropped = prune(X_train, y_train)
```

Phase 3 - Logistic Model

The function outputs a list of pruned features, together with the associated p-value or vif value. The function returns the pruned model, together with a list of pruned feature names.

```
dropping   DJI_DAILY_RETURNS with p-value 0.7234766099770011
dropping GDAXI_DAILY_RETURNS with p-value 0.6162105670376612
dropping       NSEI_HL_RATIO with p-value 0.4277618505298021
dropping        DJI_HL_RATIO with p-value 0.1563055988923202
dropping  NSEI_DAILY_RETURNS with p-value 0.13281329048460666
dropping            NSEI_TSI with     vif 5.865700460659149
dropping            NSEI_RSI with p-value 0.7783762272653001
```

Phase 3 - Logistic Model

The Logistic Model Summary

Dep. Variable:	NSEI_OPEN_DIR	**No. Observations:**	1220
Model:	Logit	**Df Residuals:**	1213
Method:	MLE	**Df Model:**	6
Date:	Wed, 10 Jul 2024	**Pseudo R-squ.:**	0.1375
Time:	10:31:02	**Log-Likelihood:**	-660.02
converged:	True	**LL-Null:**	-765.23
Covariance Type:	nonrobust	**LLR p-value:**	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

Phase 3 - Logistic Model

The final model is:

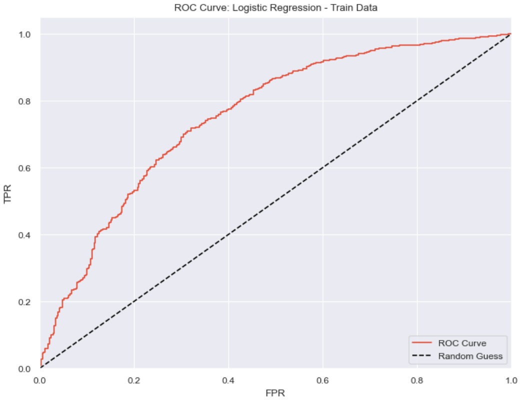
$$ln\left(\frac{p}{1-p}\right) = -1.4041 + 0.4552x_1 - 0.1395x_2 - 0.1960x_3 - 0.0397x_4 + 0.0447x_5 - 0.0205x_6$$

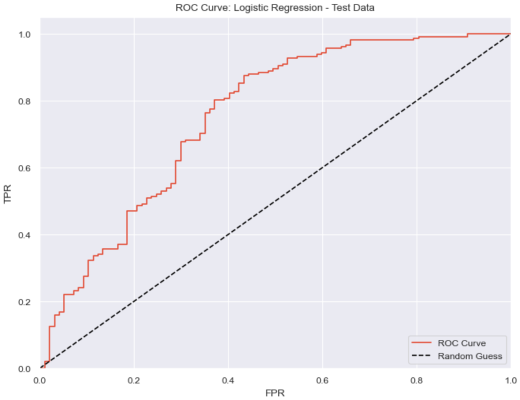
where:

variable	value
x_1	IXIC_DAILY_RETURNS
x_2	HSI_DAILY_RETURNS
x_3	N225_DAILY_RETURNS
x_4	VIX_DAILY_RETURNS
x_5	DJI_RSI
x_6	DJI_TSI

Phase 3 - Logistic Model

We plot the ROC curve for the train and test data:





Phase 3 - Logistic Model

The classification report and confusion matrix for the train data:

```
Train Data - Classification Report:

              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


Train Data - Confusion Matrix:

NSEI_OPEN_DIR  0.0  1.0
row_0
0              265  234
1              126  595
```

Phase 3 - Logistic Model

The classification report and confusion matrix for the test data:

```
Test Data - Classification Report:

              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


Test Data - Confusion Matrix:

NSEI_OPEN_DIR  0.0  1.0
row_0
0               63   57
1               34  151
```

Phase 3 - Logistic Model

We compare some statistics across train and test data:

```
Train Data - Sensitivity: 71.77%
 Test Data - Sensitivity: 72.6%

Train Data - Specificity: 67.77%
 Test Data - Specificity: 64.95%

Train Data - AUC ROC: 0.753
 Test Data - AUC ROC: 0.752
```

Phase 3 - Logistic Model

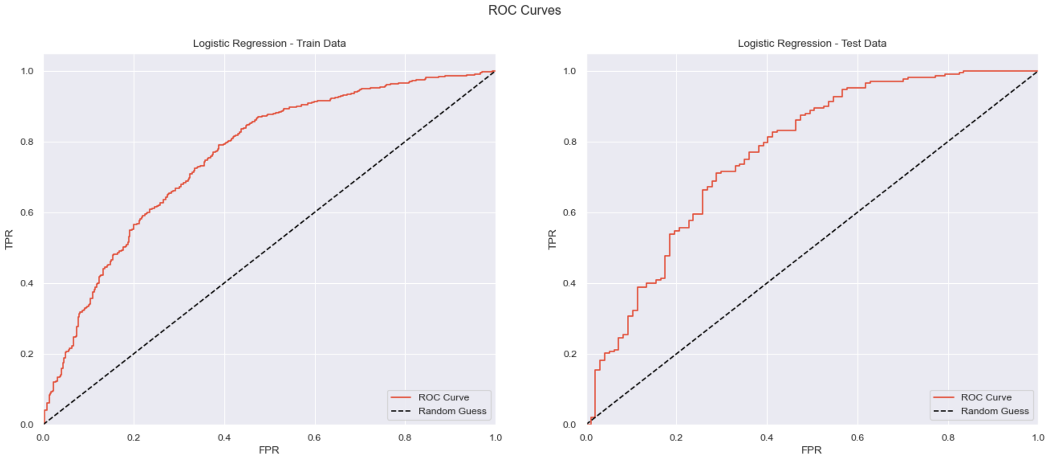
The AUC is consistent across the train and test data, and the sensitivity and specificity values are reasonably good, and somewhat consistent across the train and test data. However, the accuracy of the model is not great. We could potentially obtain better results by selecting a different approach to classification.

Phase 4 - Compare Models

We compare the performance of a number of different models to see if we can improve on the accuracy of our original model:

- Logistic Regression
- Naive Bayes
- KNN
- Decision Tree
- Random Forest
- SVM
- MLP
- Deep Learning (PyTorch)

Logistic Regression



Phase 4 - Compare Models

Logistic Regression

```
Train Data - Classification Report:

              precision    recall  f1-score   support

         0.0       0.58      0.61      0.59       391
         1.0       0.81      0.79      0.80       829

    accuracy                           0.73      1220
   macro avg       0.70      0.70      0.70      1220
weighted avg       0.74      0.73      0.73      1220


Train Data - Confusion Matrix:

col_0  0.0  1.0
row_0
0      239  174
1      152  655
```

Phase 4 - Compare Models

Logistic Regression

```
 Test Data - Classification Report:

              precision    recall  f1-score   support

         0.0       0.56      0.63      0.59        97
         1.0       0.82      0.77      0.79       208

    accuracy                           0.72       305
   macro avg       0.69      0.70      0.69       305
weighted avg       0.73      0.72      0.73       305


 Test Data - Confusion Matrix:

col_0  0.0  1.0
row_0
0       61   48
1       36  160
```

Phase 4 - Compare Models

Logistic Regression

```
Train Data - Sensitivity: 79.01%
 Test Data - Sensitivity: 76.92%

Train Data - Specificity: 61.13%
 Test Data - Specificity: 62.89%

Train Data - AUC ROC: 0.758
 Test Data - AUC ROC: 0.767
```

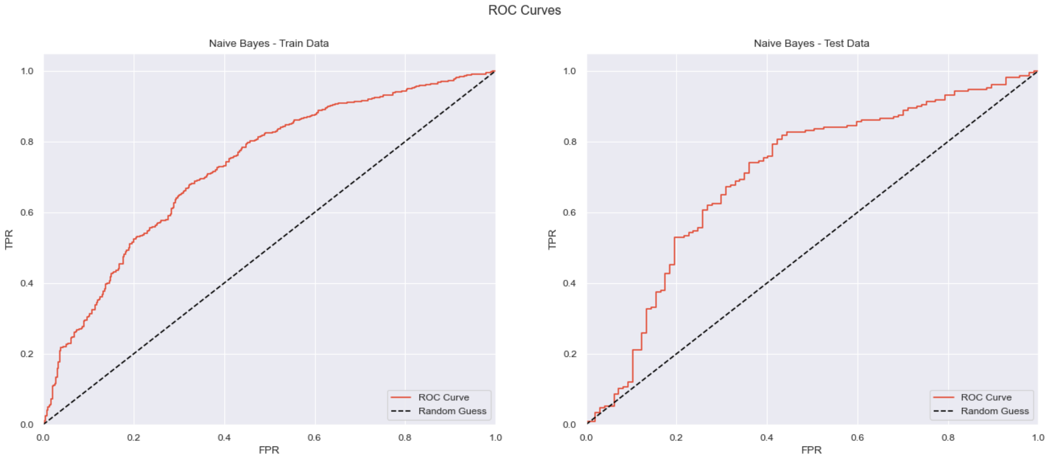
Phase 4 - Compare Models

We notice that the scikit-learn Logistic Regression model slightly outperforms the Statsmodels Logit model.

We use the Statsmodels Logit model when we need to perform analysis of the model and features, then move to scikit-learn's LogisticRegression model after the model has been finalised.

Phase 4 - Compare Models

Naive Bayes



Phase 4 - Compare Models

Naive Bayes

```
Train Data - Classification Report:

              precision    recall  f1-score   support

         0.0       0.50      0.68      0.57       391
         1.0       0.82      0.68      0.74       829

    accuracy                           0.68      1220
   macro avg       0.66      0.68      0.66      1220
weighted avg       0.71      0.68      0.69      1220


Train Data - Confusion Matrix:

col_0  0.0  1.0
row_0
0      264  266
1      127  563
```

Phase 4 - Compare Models

Naive Bayes

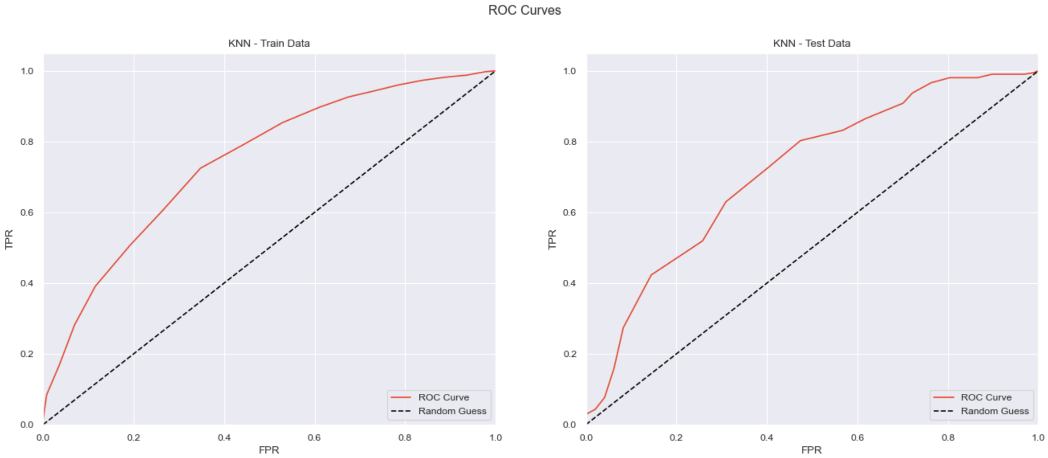
```
 Test Data - Classification Report:

              precision    recall  f1-score   support

         0.0       0.47      0.70      0.56        97
         1.0       0.82      0.62      0.71       208

    accuracy                           0.65       305
   macro avg       0.64      0.66      0.63       305
weighted avg       0.71      0.65      0.66       305


 Test Data - Confusion Matrix:

col_0  0.0  1.0
row_0
0       68   78
1       29  130
```

Phase 4 - Compare Models

Naive Bayes

```
Train Data - Sensitivity: 67.91%
 Test Data - Sensitivity: 62.5%

Train Data - Specificity: 67.52%
 Test Data - Specificity: 70.1%

Train Data - AUC ROC: 0.728
 Test Data - AUC ROC: 0.702
```

KNN


ROC Curves
KNN - Train Data
KNN - Test Data
TPR
FPR
1.0
0.8
0.6
0.4
0.2
0.0
ROC Curve
Random Guess

KNN

Train Data - Classification Report:

	precision	recall	f1-score	support
0.0	0.47	0.74	0.57	391
1.0	0.83	0.60	0.70	829
accuracy			0.65	1220
macro avg	0.65	0.67	0.64	1220
weighted avg	0.71	0.65	0.66	1220

Train Data - Confusion Matrix:

NSEI_OPEN_DIR	0.0	1.0
row_0		
0	288	328
1	103	501

Phase 4 - Compare Models

KNN

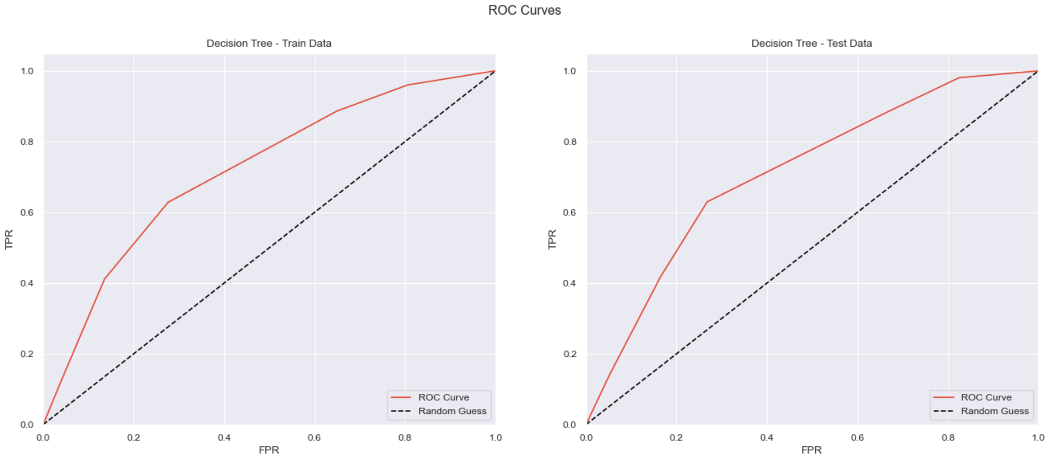
```
 Test Data - Classification Report:

              precision    recall  f1-score   support

         0.0       0.47      0.69      0.56        97
         1.0       0.81      0.63      0.71       208

    accuracy                           0.65       305
   macro avg       0.64      0.66      0.63       305
weighted avg       0.70      0.65      0.66       305


 Test Data - Confusion Matrix:

NSEI_OPEN_DIR  0.0  1.0
row_0
0               67   77
1               30  131
```

Phase 4 - Compare Models

KNN

```
Train Data - Sensitivity: 60.43%
 Test Data - Sensitivity: 62.98%

Train Data - Specificity: 73.66%
 Test Data - Specificity: 69.07%

Train Data - AUC ROC: 0.745
 Test Data - AUC ROC: 0.716
```

Decision Tree



Phase 4 - Compare Models

Decision Tree

```
Train Data - Classification Report:

              precision    recall  f1-score   support

         0.0       0.41      0.86      0.56       391
         1.0       0.87      0.41      0.56       829

    accuracy                           0.56      1220
   macro avg       0.64      0.64      0.56      1220
weighted avg       0.72      0.56      0.56      1220


Train Data - Confusion Matrix:

NSEI_OPEN_DIR  0.0  1.0
row_0
0              338  488
1               53  341
```

Decision Tree

```
 Test Data - Classification Report:

              precision    recall  f1-score   support

         0.0       0.40      0.84      0.54        97
         1.0       0.84      0.42      0.56       208

    accuracy                           0.55       305
   macro avg       0.62      0.63      0.55       305
weighted avg       0.70      0.55      0.55       305


 Test Data - Confusion Matrix:

NSEI_OPEN_DIR  0.0  1.0
row_0
0               81  121
1               16   87
```

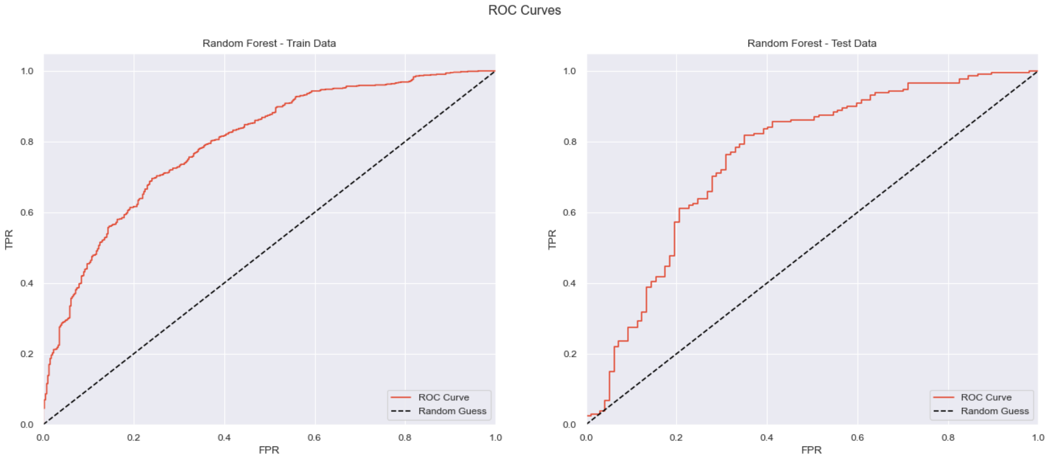
Phase 4 - Compare Models

Decision Tree

```
Train Data - Sensitivity: 41.13%
 Test Data - Sensitivity: 41.83%

Train Data - Specificity: 86.45%
 Test Data - Specificity: 83.51%

Train Data - AUC ROC: 0.719
 Test Data - AUC ROC: 0.712
```

Phase 4 - Compare Models

Random Forest



Phase 4 - Compare Models

Random Forest

```
Train Data - Classification Report:

              precision    recall  f1-score   support

         0.0       0.54      0.76      0.63       391
         1.0       0.86      0.69      0.77       829

    accuracy                           0.71      1220
   macro avg       0.70      0.73      0.70      1220
weighted avg       0.76      0.71      0.72      1220


Train Data - Confusion Matrix:

NSEI_OPEN_DIR  0.0  1.0
row_0
0              297  254
1               94  575
```

Phase 4 - Compare Models

Random Forest

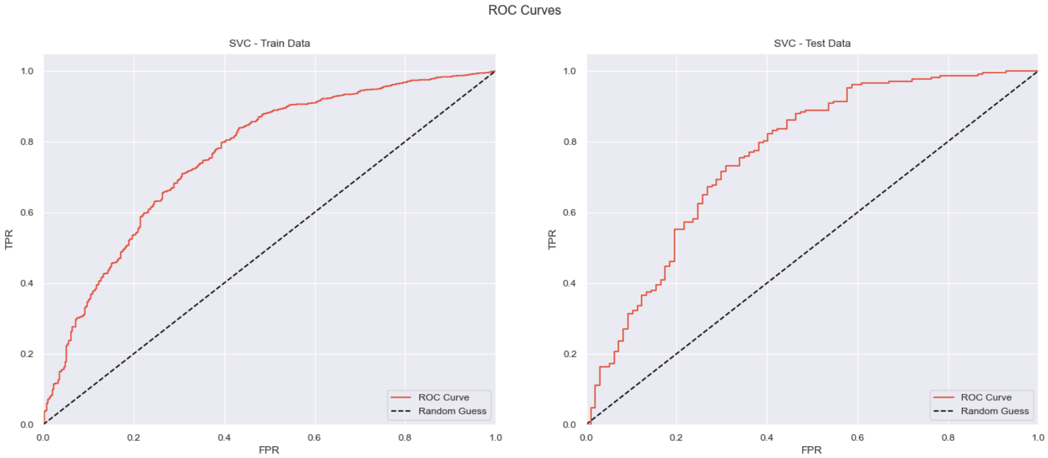
```
 Test Data - Classification Report:

              precision    recall  f1-score   support

         0.0       0.51      0.72      0.60        97
         1.0       0.84      0.68      0.75       208

    accuracy                           0.69       305
   macro avg       0.68      0.70      0.67       305
weighted avg       0.73      0.69      0.70       305


 Test Data - Confusion Matrix:

NSEI_OPEN_DIR  0.0  1.0
row_0
0               70   67
1               27  141
```

Phase 4 - Compare Models

Random Forest

```
Train Data - Sensitivity: 69.36%
 Test Data - Sensitivity: 67.79%

Train Data - Specificity: 75.96%
 Test Data - Specificity: 72.16%

Train Data - AUC ROC: 0.796
 Test Data - AUC ROC: 0.756
```

SVM


ROC Curves
SVC - Train Data
SVC - Test Data
TPR
FPR
0.0
0.2
0.4
0.6
0.8
1.0
ROC Curve
Random Guess

Phase 4 - Compare Models

SVM

Train Data - Classification Report:

	precision	recall	f1-score	support
0.0	0.62	0.57	0.59	391
1.0	0.80	0.84	0.82	829
accuracy			0.75	1220
macro avg	0.71	0.70	0.71	1220
weighted avg	0.75	0.75	0.75	1220

Train Data - Confusion Matrix:

NSEI_OPEN_DIR	0.0	1.0
row_0		
0	222	136
1	169	693

Phase 4 - Compare Models

SVM

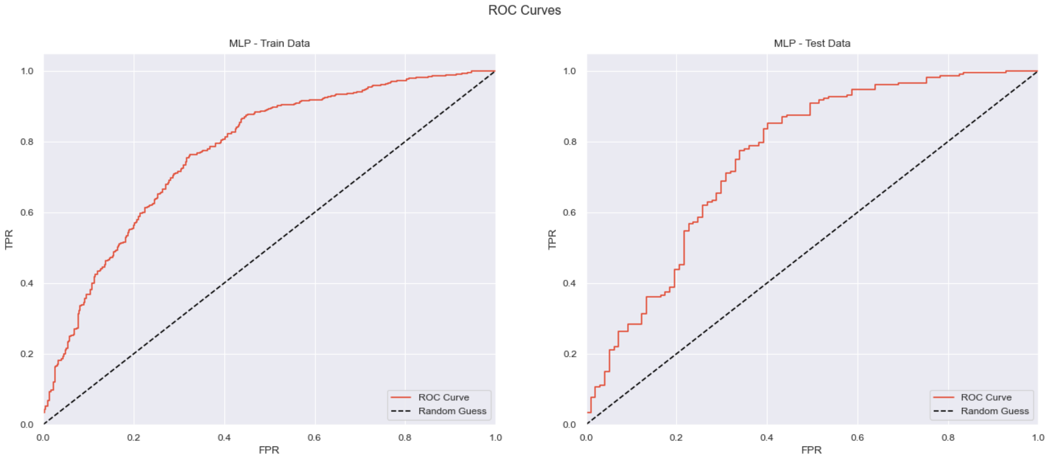
```
 Test Data - Classification Report:

              precision    recall  f1-score   support

         0.0       0.61      0.59      0.60        97
         1.0       0.81      0.82      0.82       208

    accuracy                           0.75       305
   macro avg       0.71      0.70      0.71       305
weighted avg       0.75      0.75      0.75       305


 Test Data - Confusion Matrix:

NSEI_OPEN_DIR  0.0  1.0
row_0
0               57   37
1               40  171
```

Phase 4 - Compare Models

SVM

```
Train Data - Sensitivity: 83.59%
 Test Data - Sensitivity: 82.21%

Train Data - Specificity: 56.78%
 Test Data - Specificity: 58.76%

Train Data - AUC ROC: 0.760
 Test Data - AUC ROC: 0.763
```

MLP


ROC Curves
MLP - Train Data
MLP - Test Data
TPR
FPR
0.0
0.2
0.4
0.6
0.8
1.0
ROC Curve
Random Guess

MLP

```
Train Data - Classification Report:

              precision    recall  f1-score   support

         0.0       0.57      0.68      0.62       391
         1.0       0.83      0.76      0.80       829

    accuracy                           0.73      1220
   macro avg       0.70      0.72      0.71      1220
weighted avg       0.75      0.73      0.74      1220


Train Data - Confusion Matrix:

NSEI_OPEN_DIR  0.0  1.0
row_0
0              264  198
1              127  631
```

MLP

```
 Test Data - Classification Report:

             precision    recall  f1-score   support

         0.0       0.55      0.67      0.60        97
         1.0       0.83      0.75      0.78       208

    accuracy                           0.72       305
   macro avg       0.69      0.71      0.69       305
weighted avg       0.74      0.72      0.73       305


 Test Data - Confusion Matrix:

NSEI_OPEN_DIR  0.0  1.0
row_0
0               65   53
1               32  155
```

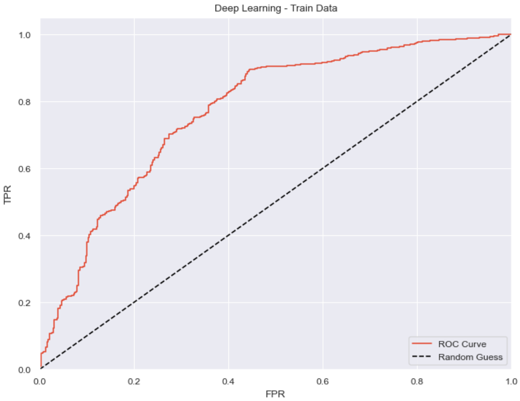
Phase 4 - Compare Models

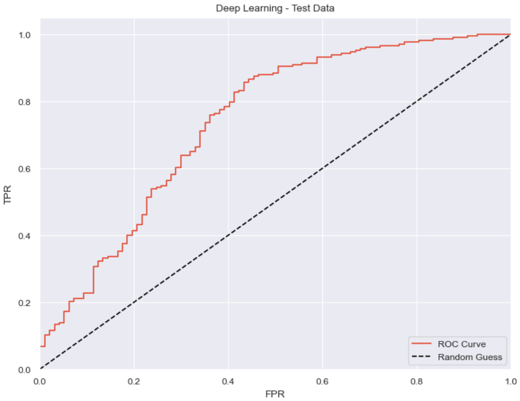
MLP

```
Train Data - Sensitivity: 76.12%
 Test Data - Sensitivity: 74.52%

Train Data - Specificity: 67.52%
 Test Data - Specificity: 67.01%

Train Data - AUC ROC: 0.773
 Test Data - AUC ROC: 0.757
```

Phase 4 - Compare Models

Deep Learning (PyTorch)





Deep Learning (PyTorch)

```
Train Data - Classification Report:

              precision    recall  f1-score   support

         0.0       0.71      0.56      0.62       391
         1.0       0.81      0.89      0.85       829

    accuracy                           0.79      1220
   macro avg       0.76      0.73      0.74      1220
weighted avg       0.78      0.79      0.78      1220


Train Data - Confusion Matrix:

col_0  0.0  1.0
row_0
0      218   89
1      173  740
```

Phase 4 - Compare Models

Deep Learning (PyTorch)

```
 Test Data - Classification Report:

              precision    recall  f1-score   support

         0.0       0.66      0.55      0.60        97
         1.0       0.80      0.87      0.84       208

    accuracy                           0.77       305
   macro avg       0.73      0.71      0.72       305
weighted avg       0.76      0.77      0.76       305


 Test Data - Confusion Matrix:

col_0  0.0  1.0
row_0
0       53   27
1       44  181
```

Phase 4 - Compare Models

Deep Learning (PyTorch)

```
Train Data - Sensitivity: 87.02%
 Test Data - Sensitivity: 89.26%

Train Data - Specificity: 54.64%
 Test Data - Specificity: 55.75%

Train Data - AUC ROC: 0.772
 Test Data - AUC ROC: 0.738
```

Phase 4 - Compare Models

```
       Naive Bayes - Test Data - AUC ROC: 0.702
     Decision Tree - Test Data - AUC ROC: 0.712
               KNN - Test Data - AUC ROC: 0.716
     Deep Learning - Test Data - AUC ROC: 0.738
     Random Forest - Test Data - AUC ROC: 0.756
               MLP - Test Data - AUC ROC: 0.757
               SVM - Test Data - AUC ROC: 0.763
Logistic Regression - Test Data - AUC ROC: 0.767
```

Interestingly, the values of AUC for each model are not indicative of the accuracy of the models - the Logistic Regression model, which had a very average accuracy, has the highest AUC, while the Deep Learning model, the model with the highest accuracy, has an average AUC.

Phase 5 - Sentiment Analysis

We now turn to Twitter / X data relating to the Nifty 50 index to see if we can mine some sentiment.

We load the tweets, create a data frame, and then do some basic pre-processing of the data to:

1. transform all words to lowercase
2. remove all punctuation
3. remove all digits
4. remove stopwords

We load the tweets:

```
with open(os.path.join(os.getcwd(), "Tweets.txt")) as file:
    tweets = [line.rstrip() for line in file]

data = pd.DataFrame(
     [line for line in tweets if len(line) > 0],
     columns= ["Tweets"]
)
data.head()
```

```
                                               Tweets
0  #bankNifty 50100 ce looks good at 70+-2 for a ...
1  "#market #banknifty #OptionsTrading #optionbuy...
2  PENNY STOCK MADHUCON PROJECTS LTD cmp-11 FOLLO...
3  #Nifty50 has been in a healthy uptrend since t...
4  #Gravita #livetrading #stockstowatch #stocksin...
```

Phase 5 - Sentiment Analysis

We perform the basic transformation:

```
stop_words    = set(stopwords.words('english'))
remove_punc   = str.maketrans('', '', punctuation)
remove_digits = str.maketrans('', '', digits)

def preprocess_tweet(tweet):
    tokens = word_tokenize(
        tweet.lower().translate(remove_punc).translate(remove_digits)
    )
    return " ".join([word for word in tokens if word not in stop_words])

cleaned = data["Tweets"].apply(preprocess_tweet)
cleaned.head()
```

```
0           banknifty ce looks good target nifty nifty
1     market banknifty optionstrading optionbuying t...
2     penny stock madhucon projects ltd cmp followht...
3     nifty healthy uptrend since beginning year did...
4     gravita livetrading stockstowatch stocksinfocu...
```

We look at the top 10 words by frequency:

```
tweet_words = cleaned.str.cat(sep = " ")

freq_dist = nltk.FreqDist(tweet_words.split())
word_freq = pd.DataFrame(freq_dist.most_common(10), columns=["Word", "Freq"])
word_freq.head(10)
```

	Word	Freq
0	nifty	399
1	banknifty	104
2	stockmarket	71
3	niftybank	45
4	stockmarketindia	44
5	sensex	43
6	stocks	38
7	optionstrading	36
8	bse	34
9	breakoutstocks	31

...

Phase 5 - Sentiment Analysis

We include the word “nifty” to list of woords to remove from the tweets:

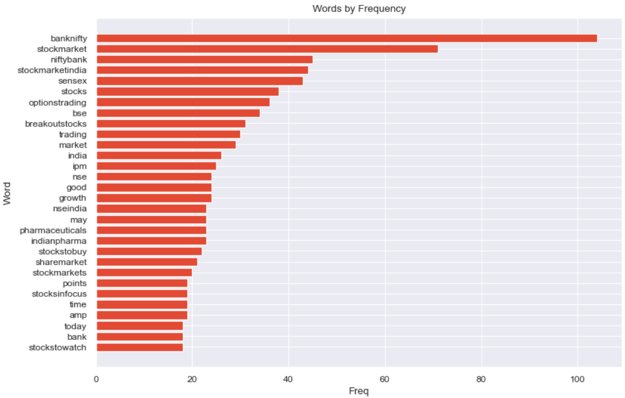
```
stop_words = set(stopwords.words('english')) | set(["nifty"])

data["Cleaned_Tweets"] = data["Tweets"].apply(preprocess_tweet)
data.head()
```

```
                                              Tweets  \
0  #bankNifty 50100 ce looks good at 70+-2 for a ...
1  "#market #banknifty #OptionsTrading #optionbuy...
2  PENNY STOCK MADHUCON PROJECTS LTD cmp-11 FOLLO...
3  #Nifty50 has been in a healthy uptrend since t...
4  #Gravita #livetrading #stockstowatch #stocksin...

                                      Cleaned_Tweets
0                   banknifty ce looks good target
1  market banknifty optionstrading optionbuying t...
2  penny stock madhucon projects ltd cmp followht...
3  healthy uptrend since beginning year didnt bre...
4  gravita livetrading stockstowatch stocksinfocu...
```

We should review more of the words as candidates to include for removal.

Phase 5 - Sentiment Analysis

We visualise these top 20 words by frequency:



Phase 5 - Sentiment Analysis

We create a word cloud:

Phase 5 - Sentiment Analysis

We extract sentiment scores for the tweets:

```
sia = SentimentIntensityAnalyzer()

scores = data["Cleaned_Tweets"].apply(lambda x: sia.polarity_scores(x))

data["Positive_Score"] = scores.apply(lambda x: x["pos"])
data["Negative_Score"] = scores.apply(lambda x: x["neg"])
data["Neutral_Score"]  = scores.apply(lambda x: x["neu"])
data["Compound_Score"] = scores.apply(lambda x: x["compound"])
```

Phase 5 - Sentiment Analysis

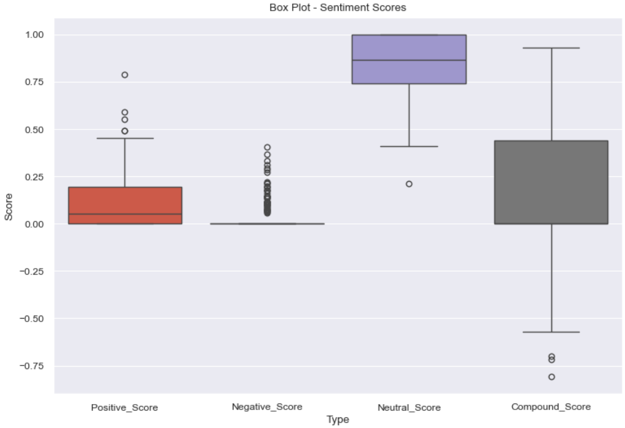
We look at the summary statistics for the sentiment scores:

	Positive_Score	Negative_Score	Neutral_Score	Compound_Score
count	245.000000	245.000000	245.000000	245.000000
mean	0.116216	0.028490	0.855314	0.172913
std	0.146029	0.071052	0.156892	0.343955
min	0.000000	0.000000	0.213000	-0.807400
25%	0.000000	0.000000	0.742000	0.000000
50%	0.053000	0.000000	0.868000	0.000000
75%	0.194000	0.000000	1.000000	0.440400
max	0.787000	0.405000	1.000000	0.928700

The compound score has a reasonable spread with a median of 0.

Phase 5 - Sentiment Analysis

We plot the sentiment scores:



Phase 5 - Sentiment Analysis

It looks like the compound sentiment scores, if slightly positively skewed, could be useful as an extra feature. This positive skewing could be understood in terms of the distribution of open directions in the data.

But in the end, without access to historical tweets, it would be impossible to judge the efficacy of the sentiment scores conclusively. Nevertheless it would appear promissing, and it should be investigated further.

Conclusion

Predicting NSEI open direction is a very interesting problem. We have shown the ability to train models with accuracy of around 75% in the case of the SVM model, and 77% - 79% in the case of the Deep Learning (PyTorch) model - I am confident that with enhanced model tuning, and by adding extra features such as sentiment compound score, we could improve the model accuracy significantly.