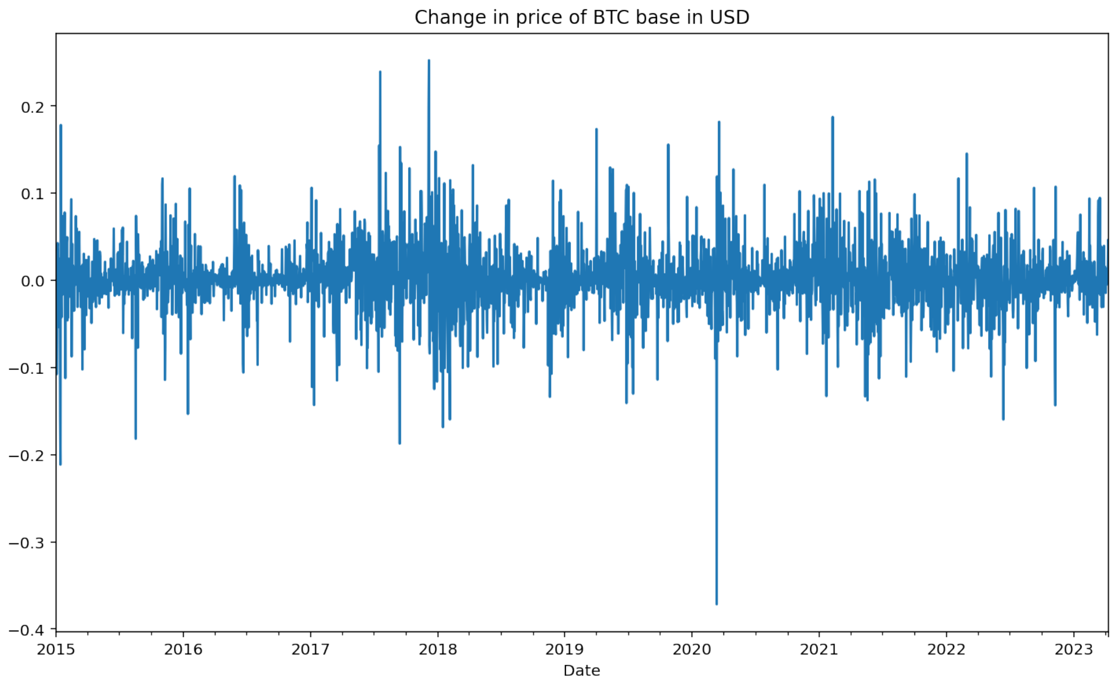
Portfolio_strategy

April 11, 2023

[56]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import yfinance as yf
import pandas_datareader as pdr
import requests_cache
session = requests_cache.CachedSession()
import scipy.optimize as sco
import seaborn as sns
import statsmodels.formula.api as smf
import statsmodels.api as sm #pip install statsmodels --upgrade
from statsmodels.tsa.arima_model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.stattools import adfuller
import statsmodels.api as sm
from scipy.stats import norm
import pandas_datareader.data as web
import arch as arch
from arch import arch_model
import statsmodels.formula.api as smf
pd.set_option('display.float_format', '{:.4f}'.format)
%precision 2
%config InlineBackend.figure_format = 'retina'
```

[58]:
```
# Import Bitcoin based in USD
tickers = 'BTC-USD '
matana = (
    yf.download(tickers=tickers, progress=False)
    .assign(Date=lambda x: x.index.tz_localize(None))
    .set_index('Date')
    .rename_axis(columns=['Ticker'])
)
returns_1 = matana['Adj Close'].pct_change().loc['2015':]
matana['return']=returns_1
# Plot the return
returns_1.plot(figsize=(12,7))
```

```
plt.title('Change in price of BTC base in USD')

ff = (
    pdr.DataReader(
        name='F-F_Research_Data_Factors_daily',
        data_source='famafrench',
        start='1900',
        session=session
    )
)
```



[60]:
```
# The Fama-French Three-Factor Model
brk = (
    yf.download(tickers='BTC-USD', progress=False)
    .assign(
        Date=lambda x: x.index.tz_localize(None),
        Ri=lambda x: x['Adj Close'].pct_change().mul(100)
    )
    .set_index('Date')
    .join(ff[0])
    .assign(RiRF = lambda x: x['Ri'] - x['RF'])
    .rename(columns={'Mkt-RF': 'MktRF'})
    .rename_axis(columns='Variable')
)
```

```python
model = smf.ols(formula='RiRF ~ MktRF + SMB + HML', data=brk.iloc[:756])
fit = model.fit()
summary = fit.summary()
summary
```

[60]:

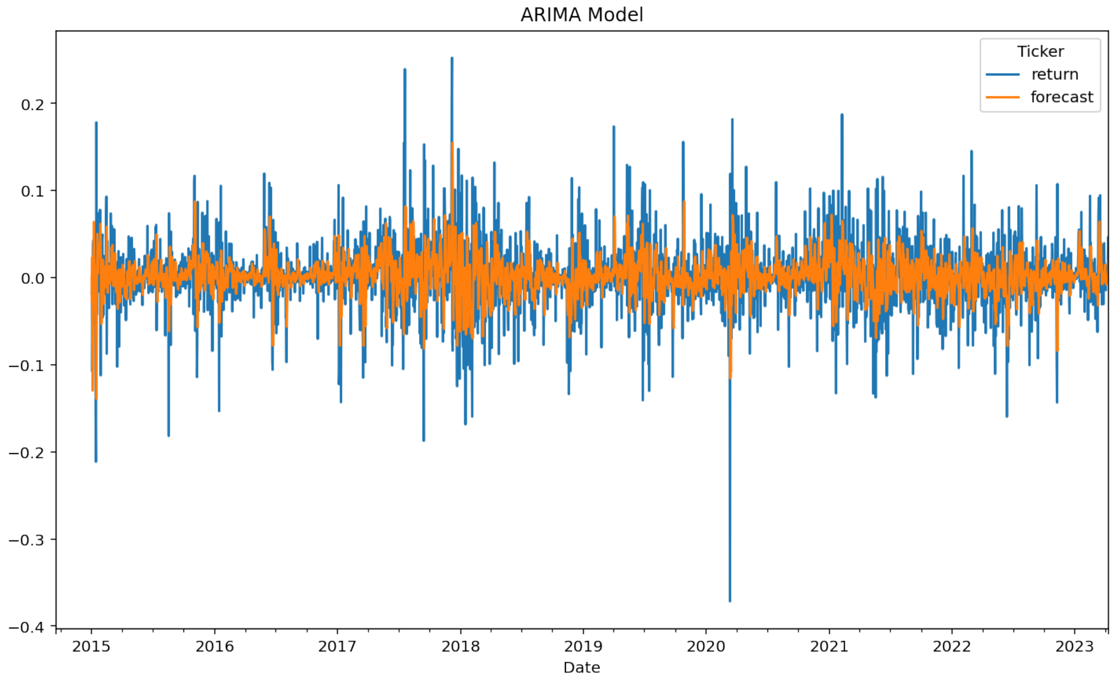
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                   RiRF   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                 -0.005
Method:                 Least Squares   F-statistic:                   0.08239
Date:                Tue, 11 Apr 2023   Prob (F-statistic):              0.970
Time:                        17:11:32   Log-Likelihood:                -1372.4
No. Observations:                 521   AIC:                             2753.
Df Residuals:                     517   BIC:                             2770.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.1010      0.148      0.681      0.496      -0.190       0.393
MktRF         -0.0718      0.158     -0.454      0.650      -0.383       0.239
SMB            0.0727      0.291      0.250      0.803      -0.499       0.644
HML            0.0225      0.290      0.078      0.938      -0.547       0.592
==============================================================================
Omnibus:                      136.317   Durbin-Watson:                   1.915
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1791.164
Skew:                          -0.738   Prob(JB):                         0.00
Kurtosis:                      11.963   Cond. No.                         2.15
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

[61]:

```python
# 1. Model ARIMA
# Order of differencing
result = adfuller(matana['Adj Close'].dropna())
print('ADF Statistic:', result[0])
print('p-value:', result[1])
diff = matana['Adj Close'].diff().dropna()
#plot_acf(diff)
#plot_pacf(diff)
#plt.show()
# Apply model: one autoregressive, one differencing, and one moving average
```

```
model = sm.tsa.arima.ARIMA(returns_1, order=(2,2,1))
results = model.fit()
print(results.summary())
matana['forecast']=results.predict()
matana[['return','forecast']].plot(figsize=(12,7))
plt.title('ARIMA Model')
warnings.filterwarnings('ignore')
```

```
ADF Statistic: -1.5051287573506575
p-value: 0.53097270747215
                               SARIMAX Results
==============================================================================
Dep. Variable:              Adj Close   No. Observations:                 3023
Model:                 ARIMA(2, 2, 1)   Log Likelihood                5149.721
Date:                Tue, 11 Apr 2023   AIC                         -10291.442
Time:                        17:14:03   BIC                         -10267.388
Sample:                    01-01-2015   HQIC                        -10282.793
                         - 04-11-2023
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.6908      0.011    -60.387      0.000      -0.713      -0.668
ar.L2         -0.3459      0.012    -28.661      0.000      -0.370      -0.322
ma.L1         -0.9999      0.098    -10.230      0.000      -1.191      -0.808
sigma2         0.0019      0.000     10.430      0.000       0.002       0.002
================================================================================
===
Ljung-Box (L1) (Q):                  22.83   Jarque-Bera (JB):
3465.30
Prob(Q):                              0.00   Prob(JB):
0.00
Heteroskedasticity (H):               0.98   Skew:
0.15
Prob(H) (two-sided):                  0.76   Kurtosis:
8.24
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```



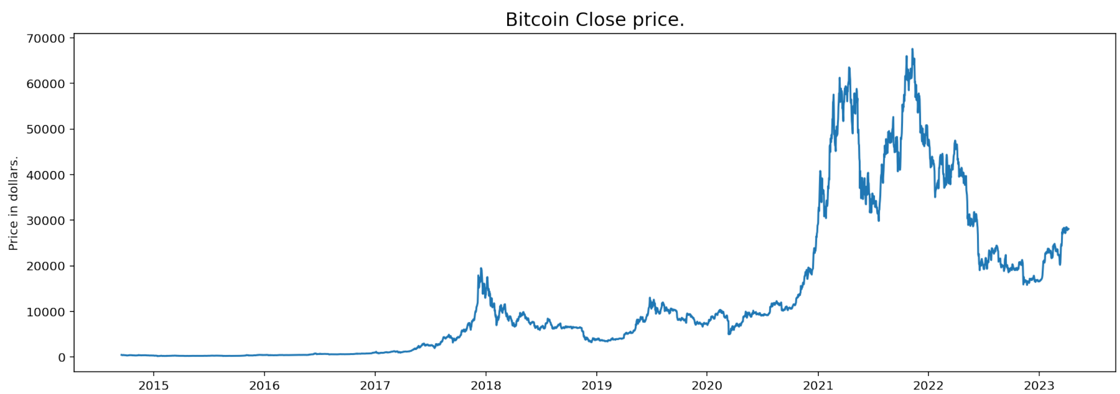
[7]:
```python
# 2. Garch Model
garch11_bitcoin = arch_model(returns_1.dropna()*100, p=1, q=1)
res_bitcoin = garch11_bitcoin.fit(update_freq=10)
print(res_bitcoin.summary())
```

```
Optimization terminated successfully    (Exit mode 0)
            Current function value: 8074.491992409081
            Iterations: 9
            Function evaluations: 60
            Gradient evaluations: 9
                     Constant Mean - GARCH Model Results
==============================================================================
Dep. Variable:              Adj Close   R-squared:                       0.000
Mean Model:             Constant Mean   Adj. R-squared:                  0.000
Vol Model:                      GARCH   Log-Likelihood:               -8074.49
Distribution:                  Normal   AIC:                           16157.0
Method:            Maximum Likelihood   BIC:                           16181.0
                                        No. Observations:                 3018
Date:                Thu, Apr 06 2023   Df Residuals:                     3017
Time:                        21:09:15   Df Model:                            1
                               Mean Model
========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
------------------------------------------------------------------------
mu             0.2247  5.727e-02      3.923  8.731e-05 [  0.112,  0.337]
```

```
                      Volatility Model
==========================================================================
                 coef    std err          t       P>|t|     95.0% Conf. Int.
--------------------------------------------------------------------------
omega          0.6647      0.237      2.806   5.022e-03   [  0.200,  1.129]
alpha[1]       0.1189  2.926e-02      4.063   4.835e-05 [6.154e-02,  0.176]
beta[1]        0.8435  2.936e-02     28.732 1.500e-181   [  0.786,  0.901]
==========================================================================

Covariance estimator: robust
```

[5]:
```python
# 3. Machine Learning model (New)
import seaborn as sb

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from xgboost import XGBClassifier #pip install xgboost
from sklearn import metrics

import warnings
warnings.filterwarnings('ignore')
```

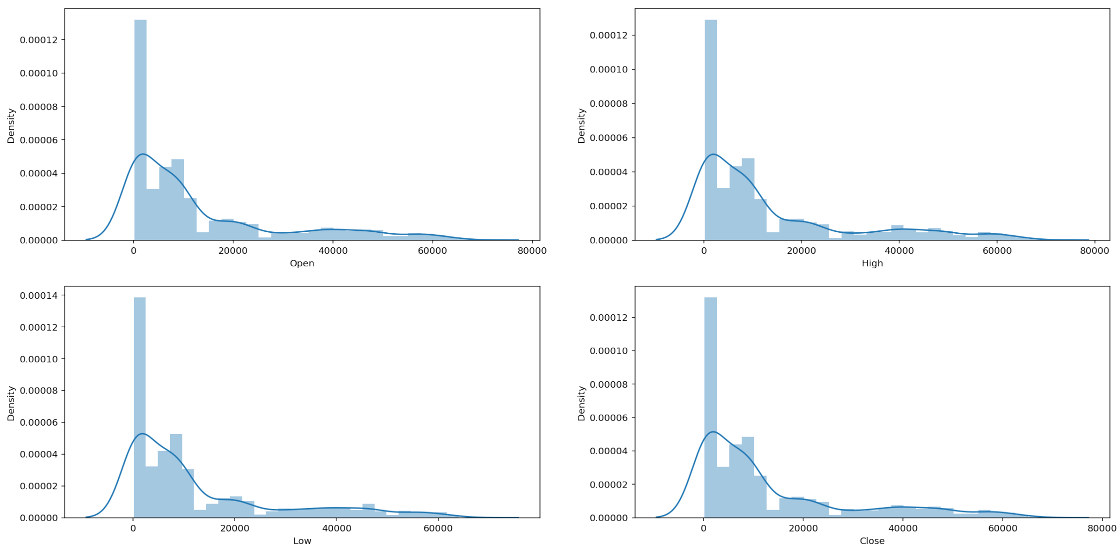
[9]:
```python
# Close data
plt.figure(figsize=(15, 5))
plt.plot(matana['Close'])
plt.title('Bitcoin Close price.', fontsize=15)
plt.ylabel('Price in dollars.')
plt.show()
```



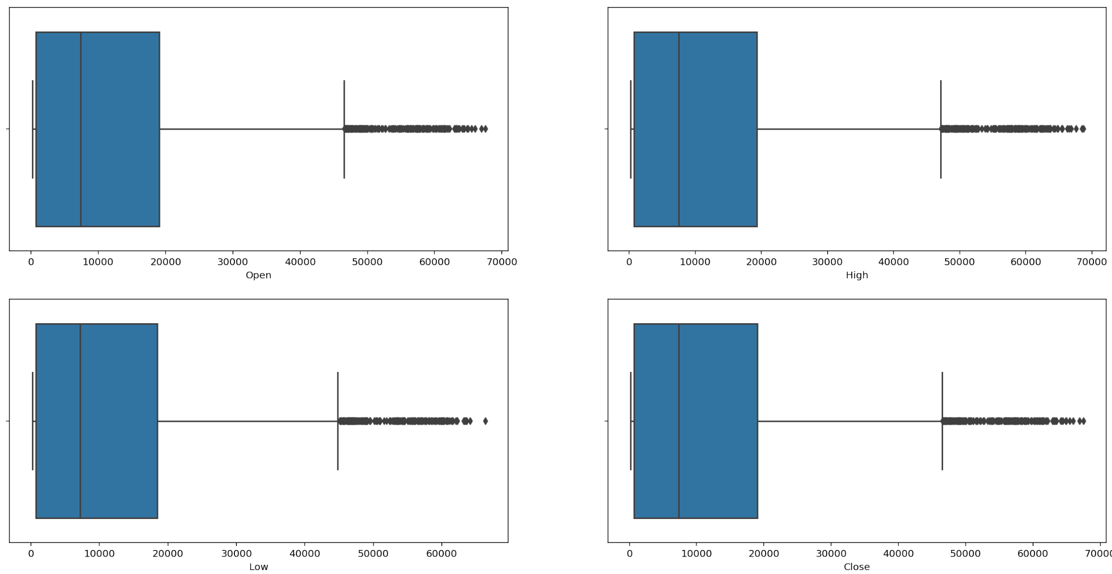
[16]:
```python
# Distribution plot of the OHLC data
features = ['Open', 'High', 'Low', 'Close']
```

```
print('Distribution plot of the OHLC data')

plt.subplots(figsize=(20,10))
for i, col in enumerate(features):
    plt.subplot(2,2,i+1)
    sb.distplot(matana[col])
plt.show()

# Boxplot of the OHLC data
print('Boxplot of the OHLC data')
plt.subplots(figsize=(20,10))
for i, col in enumerate(features):
    plt.subplot(2,2,i+1)
    sb.boxplot(matana[col])
plt.show()
```

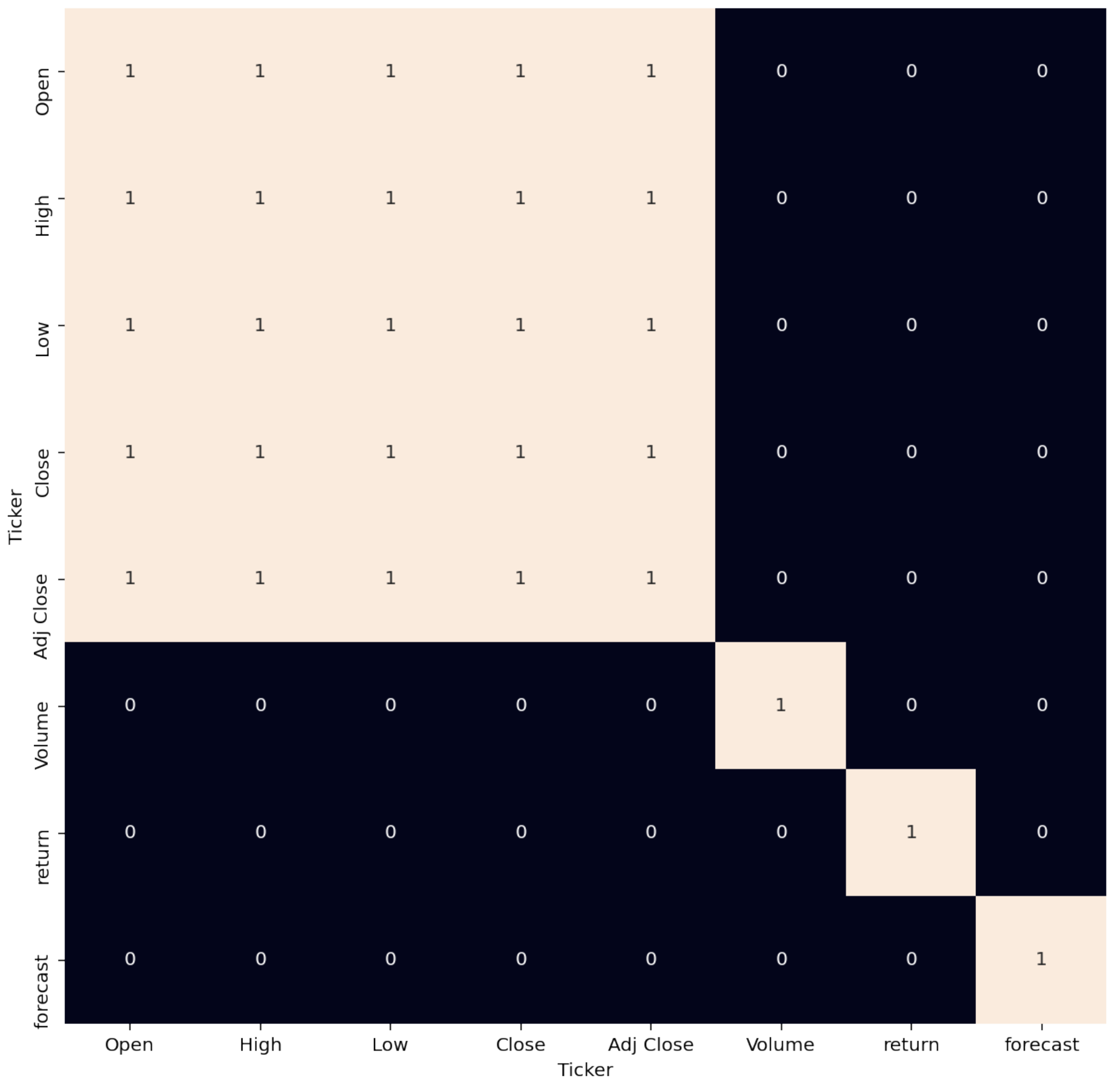
Distribution plot of the OHLC data



Boxplot of the OHLC data



[17]:
```
# Heat map
plt.figure(figsize=(10, 10))
# As our concern is with the highly correlated features only so
sb.heatmap(matana.corr() > 0.9, annot=True, cbar=False)
plt.show()
```

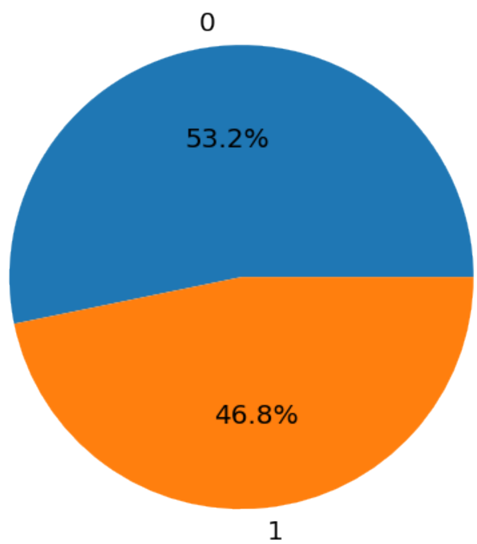


From the above heatmap, we can say that there is a high correlation between OHLC which is pretty obvious, and the added features are not highly correlated

[44]:
```
btc = pd.read_csv('BTC.csv')
```

[50]:
```
splitted = btc['Date'].str.split('/', expand=True)
# split data
btc['year'] = splitted[0].astype('int')
btc['month'] = splitted[1].astype('int')
btc['day'] = splitted[2].astype('int')

# Prepare the training of our model
btc['is_quarter_end'] = np.where(btc['month']%3==0,1,0)
btc['open-close']  = btc['Open'] - btc['Close']
```

```
btc['low-high']  = btc['Low'] - btc['High']
# target is a signal whether to buy or not
btc['target'] = np.where(btc['Close'].shift(-1) > btc['Close'], 1, 0)

# Check No correlated features
plt.pie(btc['target'].value_counts().values,
        labels=[0, 1], autopct='%1.1f%%')
plt.show()
```




```
[53]: # Training Size
features = btc[['open-close', 'low-high', 'is_quarter_end']]
target = btc['target']

scaler = StandardScaler()
features = scaler.fit_transform(features)

X_train, X_valid, Y_train, Y_valid = train_test_split(
    features, target, test_size=0.1, random_state=2022)
print(X_train.shape, X_valid.shape)
```

```
(2813, 3) (313, 3)
```

we normalize the date and split into two parts with a 90/10 ratio so, that we can evaluate the performance of our model on unseen data.

```
[54]: # Apply the model with LogisticRegression, SVC, XGBClassifier
# Performance of different state-of-the-art models.
```

```
models = [LogisticRegression(), SVC(kernel='poly', probability=True),␣
 ↪XGBClassifier()]

for i in range(3):
    models[i].fit(X_train, Y_train)
    print(f'{models[i]} : ')
    print('Training Accuracy : ', metrics.roc_auc_score(Y_train, models[i].
 ↪predict_proba(X_train)[:,1]))
    print('Validation Accuracy : ', metrics.roc_auc_score(Y_valid, models[i].
 ↪predict_proba(X_valid)[:,1]))
    print('\n')
```

```
LogisticRegression() :
Training Accuracy :  0.5296558035487315
Validation Accuracy :  0.48965742784727334


SVC(kernel='poly', probability=True) :
Training Accuracy :  0.4626005389191113
Validation Accuracy :  0.5178235630774262


XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, …) :
Training Accuracy :  0.946875031775891
Validation Accuracy :  0.4970975390401439
```

Apply the machine learning models(Logistic Regression, Support Vector Machine, XGBClassifier). For the evaluation metric, we will use the ROC-AUC curve, instead of hard probability that is 0 or 1 we would like it to predict soft probabilities that are continuous values between 0 to 1. And with soft probabilities, the ROC-AUC curve is generally used to measure the accuracy of the predictions.

Result: Among the three models, we have trained XGBClassifier has the highest performance but it is pruned to overfitting as the difference between the training and the validation accuracy is too high. Possible reasons for this may be the lack of data or using a very simple model to perform such a complex task as Stock Market prediction.

```
[ ]:
```