Stock Market Prediction Using ARIMA in Python

Finance Analytics Project

```
import pandas as pd
import numpy as np
import math

import matplotlib.pyplot as plt
import seaborn as sns
from pylab import rcParams

import statsmodels.api as sm
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.arima.model import ARIMA
from pmdarima.arima import auto_arima

from sklearn.metrics import mean_squared_error, mean_absolute_error
```

```
df = pd.read_csv('HCLTECH.NS.csv')
df.head()
```

	Date	Open	High	Low	Close	Adj Close	Volume
0	2017-04-21	408.500000	410.725006	403.899994	406.375000	358.572723	1780310
1	2017-04-24	406.500000	412.000000	404.625000	409.774994	361.572754	1373968
2	2017-04-25	412.000000	412.924988	406.799988	409.975006	361.749268	2194602
3	2017-04-26	410.950012	411.000000	398.274994	400.125000	353.057892	1918248
4	2017-04-27	398.500000	410.000000	398.100006	404.850006	357.227112	5640334

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1235 entries, 0 to 1234
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       1235 non-null   object
 1   Open       1235 non-null   float64
 2   High       1235 non-null   float64
 3   Low        1235 non-null   float64
 4   Close      1235 non-null   float64
 5   Adj Close  1235 non-null   float64
 6   Volume     1235 non-null   int64
dtypes: float64(5), int64(1), object(1)
memory usage: 67.7+ KB
```

Data Cleaning and Transformation

Removing duplicated date values if any

```
df[df["Date"].duplicated(keep = False)]
df = df[~df["Date"].duplicated()]
```

Null check to identify missing values

```
df.isnull().sum()/len(df)
```

```
Date         0.0
Open         0.0
High         0.0
Low          0.0
Close        0.0
Adj Close    0.0
Volume       0.0
dtype: float64
```

Transforming 'Date' column to index

```
df.index = pd.to_datetime(df["Date"])
data = df[df.columns[1:]]
data.head()
```

Date	Open	High	Low	Close	Adj Close	Volume
2017-04-21	408.500000	410.725006	403.899994	406.375000	358.572723	1780310
2017-04-24	406.500000	412.000000	404.625000	409.774994	361.572754	1373968
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Data Visualization

We consider 'Adj Close' column to predict the future stock price, and it looks like below:

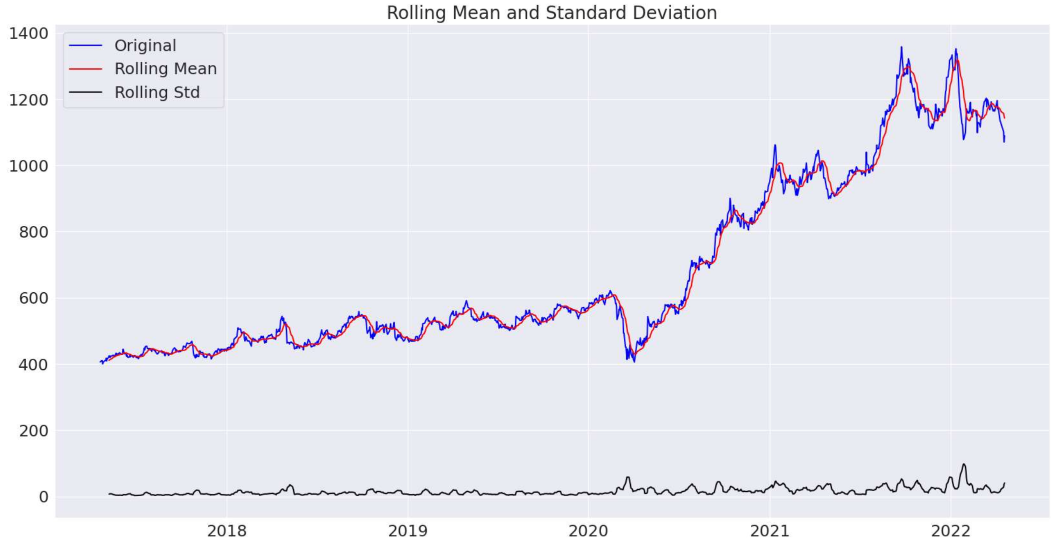
```
plt.figure(figsize = (20, 10))
sns.set_style('darkgrid')
plt.xlabel('Date', fontsize = 20)
plt.ylabel('Close Price', fontsize = 20)
plt.title('HCL Stock Market Closing Price', fontsize = 20)
plt.plot(data['Close'])
plt.tick_params(axis = 'x', labelsize = 18)
plt.tick_params(axis = 'y', labelsize = 18)
plt.savefig('AdjClose_TimeSeriesPlot.png')
```

ADF Test to check if data is Stationary or not

```
def test_adf(timeseries):
    moving_average = timeseries.rolling(12).mean()
    moving_std = timeseries.rolling(12).std()
    plt.figure(figsize = (20,10))
    plt.plot(timeseries, color = 'blue', label = 'Original')
    plt.plot(moving_average, color = 'red', label = 'Rolling Mean')
    plt.plot(moving_std, color = 'black', label = 'Rolling Std')
    plt.legend(loc = 'best', fontsize = 18)
```

```
plt.title('Rolling Mean and Standard Deviation', fontsize = 20)
plt.tick_params(axis = 'x', labelsize = 18)
plt.tick_params(axis = 'y', labelsize = 18)
plt.savefig('ADFTest2.png')
plt.show(block = False)
print("Results of Dicky Fuller Test")
adft = adfuller(timeseries, autolag = 'AIC')
output = pd.Series(adft[0:4], index = ['Test Statistics', 'p-value', 'No. of lags used', 'Number of observations used'])
for key, value in adft[4].items():
    output['Critical value (%s)' %key] = value
print(output)
```

```
test_adf(data['Close'])
```



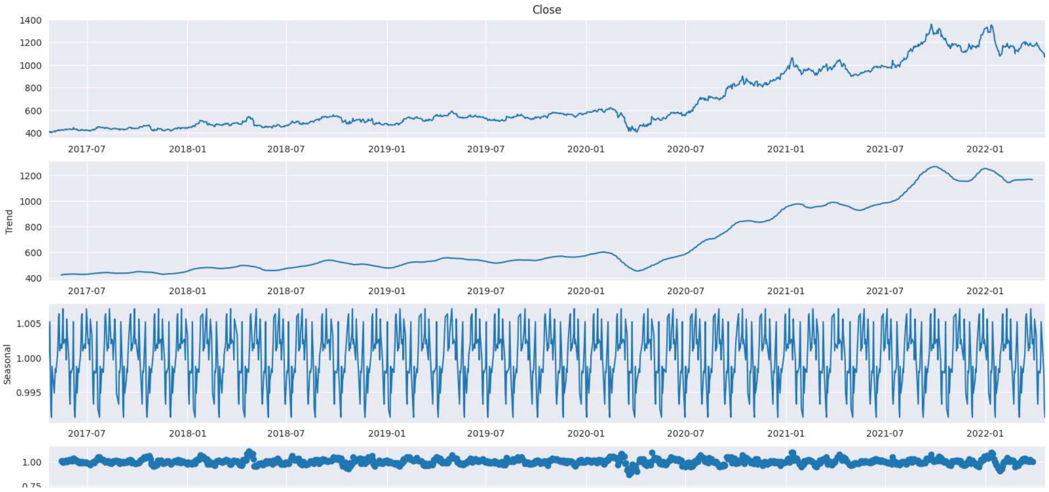

```
Results of Dicky Fuller Test
Test Statistics                  -0.684578
p-value                           0.850704
No. of lags used                  7.000000
Number of observations used    1227.000000
Critical value (1%)              -3.435691
Critical value (5%)              -2.863898
Critical value (10%)             -2.568026
dtype: float64
```

From the above result, it is evident that test Statistics is greater than the critical values and p>0.05, hence we fail to reject the null hypothesis meaning our data is non-stationary.

From the time series data, let's seperate trend and seasonality

```
result = seasonal_decompose(data['Close'], model = 'multiplicative', period = 30)
fig = plt.figure()
fig = result.plot()
fig.savefig('stationaryData.png')
fig.set_size_inches(16, 9)
```

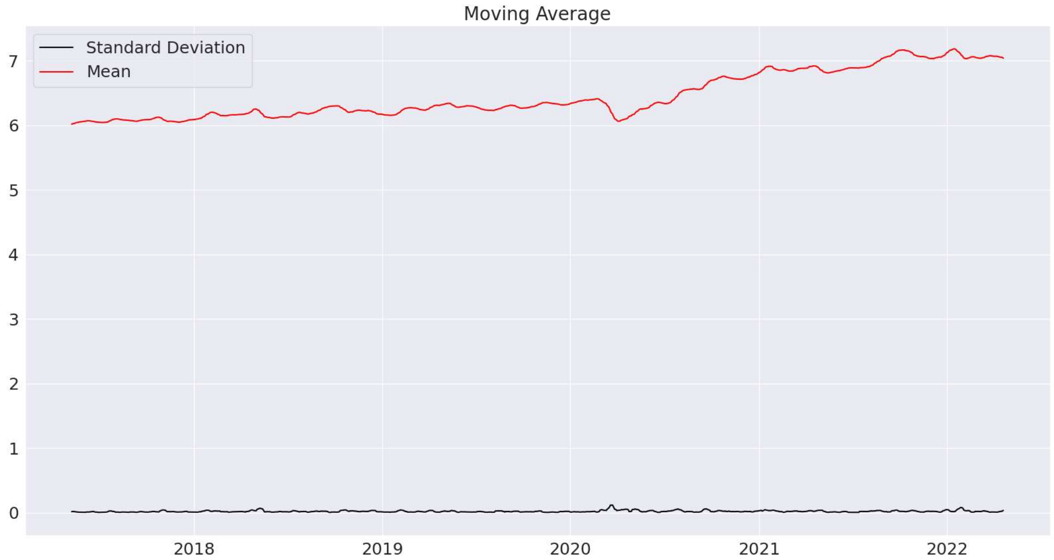
```
<Figure size 2000x1000 with 0 Axes>
```



Converting Non-stationary to Stationary Data

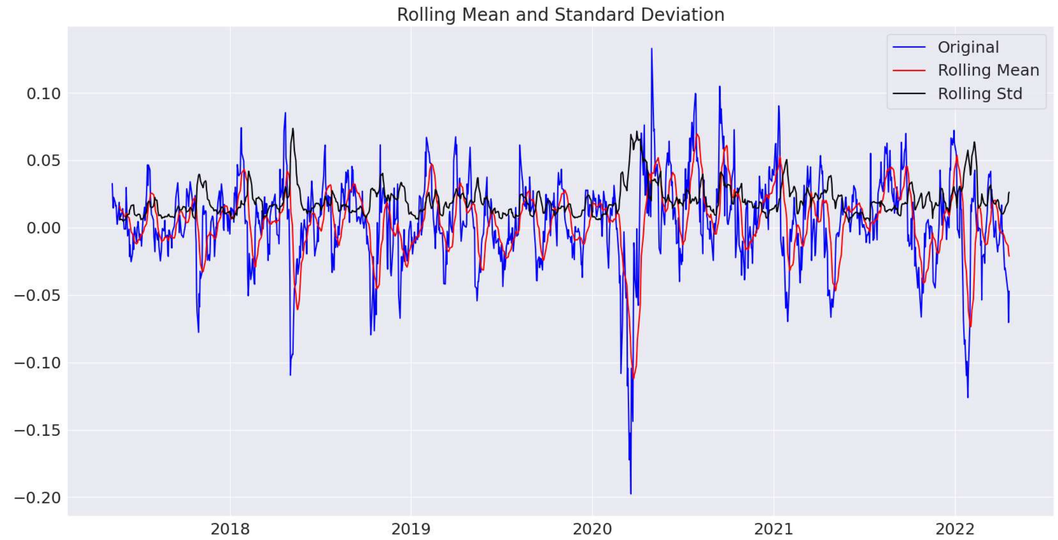
```
rcParams['figure.figsize'] = 20, 10
data_adj_close_log = np.log(data['Close'])
moving_average = data_adj_close_log.rolling(12).mean()
std_dev = data_adj_close_log.rolling(12).std()
plt.legend(loc = 'best')
plt.title('Moving Average', fontsize = 20)
plt.plot(std_dev, color = "black", label = "Standard Deviation")
plt.plot(moving_average, color = "red", label = "Mean")
plt.legend(fontsize = 18)
plt.tick_params(axis = 'x', labelsize = 18)
plt.tick_params(axis = 'y', labelsize = 18)
plt.show()
```

```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  Note that artists whose label
```



Now substract the moving average from that, and we apply ADF test.

```
data_log_minus_mean = data_adj_close_log - moving_average
data_log_minus_mean.dropna(inplace=True)
test_adf(data_log_minus_mean)
```



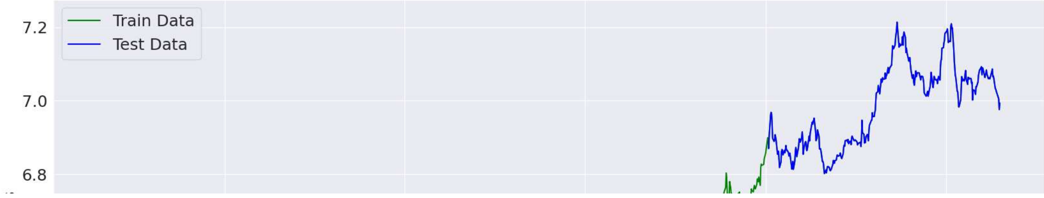

```
Results of Dicky Fuller Test
Test Statistics                 -7.958585e+00
p-value                          2.990744e-12
No. of lags used                 2.300000e+01
Number of observations used      1.200000e+03
Critical value (1%)             -3.435811e+00
Critical value (5%)             -2.863952e+00
Critical value (10%)            -2.568054e+00
dtype: float64
```

It is evident that test statistics is less than the critical values and p<0.05, hence we reject the null hypothesis meaning our time series data is stationary.

Train-Test Split

We split our train test data by the ration of 75:25.

```
train_data, test_data = data_adj_close_log[:int(len(data_adj_close_log)*0.75)], data_adj_close_log[int(len(data_log_minus_mean)*0.75):
plt.figure(figsize = (20,10))
plt.xlabel('Dates', fontsize = 18)
plt.ylabel('Closing Prices', fontsize = 18)
plt.plot(data_adj_close_log, 'green', label = 'Train Data')
plt.plot(test_data, 'blue', label = 'Test Data')
plt.legend(fontsize = 18)
plt.tick_params(axis = 'x', labelsize = 18)
plt.tick_params(axis = 'y', labelsize = 18)
plt.savefig('train-test.png')
```



Apply auto_arima function

auto_arima function helps to find an optimal order for an ARIMA model. It returns the best ARIMA model

```
model_autoARIMA = auto_arima(train_data,
                              start_p = 0, start_q = 0,
                              test = 'adf',
                              max_p = 7, max_q = 7,
                              start_P = 0, D = 0,
                              m = 1,
                              d = None,
                              seasonal = False,
                              trace = True,
                              error_action = 'ignore',
                              suppress_warnings = True,
                              stepwise = True
                             )
```

```
Performing stepwise search to minimize aic
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=-4762.672, Time=0.14 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=-4766.643, Time=0.33 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=-4767.001, Time=0.35 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=-4762.192, Time=0.13 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=-4765.326, Time=0.39 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=-4765.527, Time=0.56 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=-4763.580, Time=2.76 sec
 ARIMA(0,1,1)(0,0,0)[0]             : AIC=-4766.030, Time=0.11 sec

Best model:  ARIMA(0,1,1)(0,0,0)[0] intercept
Total fit time: 4.804 seconds
```

```
model_autoARIMA.summary()
```

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	926
Model:	SARIMAX(0, 1, 1)	**Log Likelihood**	2386.501
Date:	Thu, 03 Aug 2023	**AIC**	-4767.001
Time:	04:17:26	**BIC**	-4752.512
Sample:	0	**HQIC**	-4761.473
	- 926		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	0.0009	0.001	1.709	0.088	-0.000	0.002
ma.L1	-0.0824	0.023	-3.633	0.000	-0.127	-0.038
sigma2	0.0003	8.48e-06	39.641	0.000	0.000	0.000

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	901.01
Prob(Q):	0.99	**Prob(JB):**	0.00
Heteroskedasticity (H):	2.58	**Skew:**	0.09
Prob(H) (two-sided):	0.00	**Kurtosis:**	7.83

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

```
from statsmodels.tsa.arima.model import ARIMA

model = ARIMA(train_data, order=(1,1,0))
fitted = model.fit()
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarning: A date index has been provided, but it
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarning: A date index has been provided, but it
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarning: A date index has been provided, but it
  self._init_dates(dates, freq)
```

```
forecast = fitted.forecast(15, alpha=0.05)
print(forecast.values)
```

```
[6.88973349 6.88968309 6.88968699 6.88968669 6.88968671 6.88968671
 6.88968671 6.88968671 6.88968671 6.88968671 6.88968671 6.88968671
 6.88968671 6.88968671 6.88968671]
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:834: ValueWarning: No supported index is available. Predi
  return get_prediction_index(
```

```
# prediction_series = pd.Series(prediction,index = test_data.index)
# fig, ax = plt.subplots(1, 1, figsize = (15, 5))
# ax.plot(data_adj_close_log)
# ax.plot(prediction_series)
# ax.fill_between(prediction_series.index,
#                 cf[0],
#                 cf[1],color='grey',alpha=.3)
```

```
prediction, confint = model_autoARIMA.predict(n_periods=test_data.shape[0], return_conf_int=True)

prediction
cf= pd.DataFrame(confint)
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:834: ValueWarning: No supported index is available. Predi
  return get_prediction_index(
```

```
fc, conf = model_autoARIMA.predict(n_periods = test_data.shape[0], return_conf_int = True)

fc_series = pd.Series(fc)

fc_series.index = test_data.index

lower_series = pd.Series(conf[:, 0], index = test_data.index)
upper_series = pd.Series(conf[:, 1], index = test_data.index)

plt.figure(figsize = (12, 5), dpi = 100)
plt.plot(train_data, label = 'training')
plt.plot(test_data, color = 'blue', label = 'Actual Stock Price')
plt.plot(fc_series, color = 'orange', label = 'Predicted Stock Price')
plt.fill_between(lower_series.index, lower_series, upper_series,
                 color = 'k', alpha = 0.05)
plt.title('HCL Stock Price Prediction')
plt.xlabel('Time', fontsize = 12)
plt.ylabel('Actual Stock Price', fontsize = 12)
plt.legend(loc = 'upper left', fontsize = 12)
plt.tick_params(axis = 'x', labelsize = 12)
plt.tick_params(axis = 'y', labelsize = 12)
plt.savefig('Forecast.png')
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:834: ValueWarning: No support
  return get_prediction_index(
```

Performance of the Model

To evaluate the model performance, perfomance metrics like Mean Squared Error(MSE), Mean Absolute Error(MAE), Root Mean Squared Error(RMSE), Mean Absolute Percentage Error(MAPE) are used.

```
mse = mean_squared_error(test_data, fc)
mae = mean_absolute_error(test_data, fc)
rmse = math.sqrt(mse)
mape = np.mean(np.abs(fc - test_data)/ np.abs(test_data))

print('MSE: '+str(mse))
print('MAE: '+str(mae))
print('RMSE: '+str(rmse))
print('MAPE: '+str(mape))
```

```
MSE: 0.00803370918155261
MAE: 0.07811002552885458
RMSE: 0.08963096106565303
MAPE: 0.01120845696536436
```

From the above output it is clear that the model is performing really well on the test dataset.

0s completed at 12:17 AM