```
In [ ]:
import pandas as pd
import numpy as np
import statsmodels.api as sm
from matplotlib import pyplot
import math
```

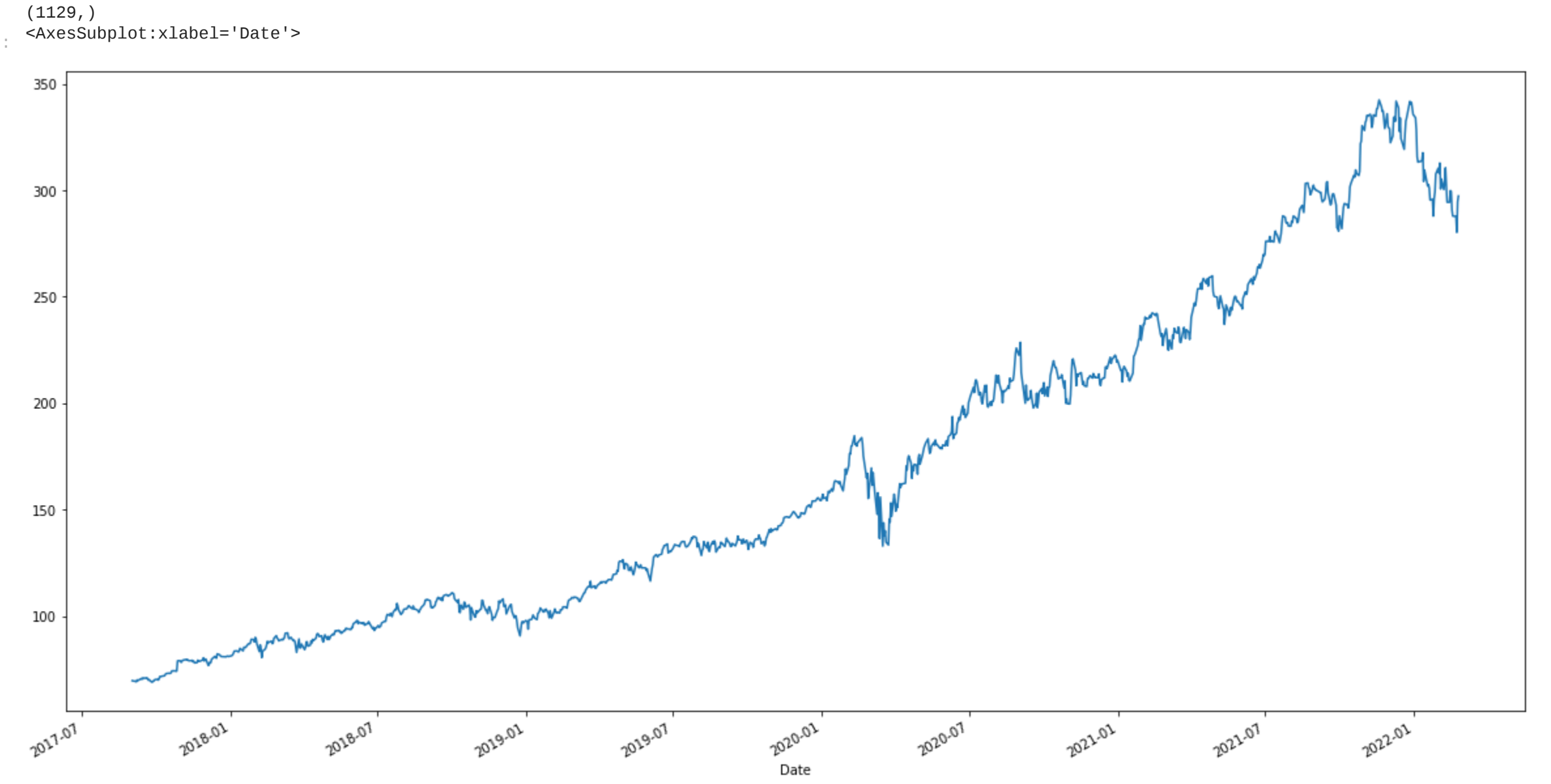
```
In [ ]:
tsData = pd.read_csv('MSFT.csv', index_col='Date', parse_dates=True)
tsData = tsData['Adj Close']
tsData = tsData.dropna()
print(tsData)
```

```
Date
2017-09-01     69.787331
2017-09-05     69.475868
2017-09-06     69.277672
2017-09-07     70.164894
2017-09-08     69.825096
                 ...
2022-02-18    287.929993
2022-02-22    287.720001
2022-02-23    280.269989
2022-02-24    294.589996
2022-02-25    297.309998
Name: Adj Close, Length: 1129, dtype: float64
```

Plotting the time series chart of USD/INR vs Time

```
In [ ]:
import matplotlib.pyplot as plt

f = plt.figure()
f.set_figwidth(20)
f.set_figheight(10)

print(tsData.shape)
tsData.plot()
```

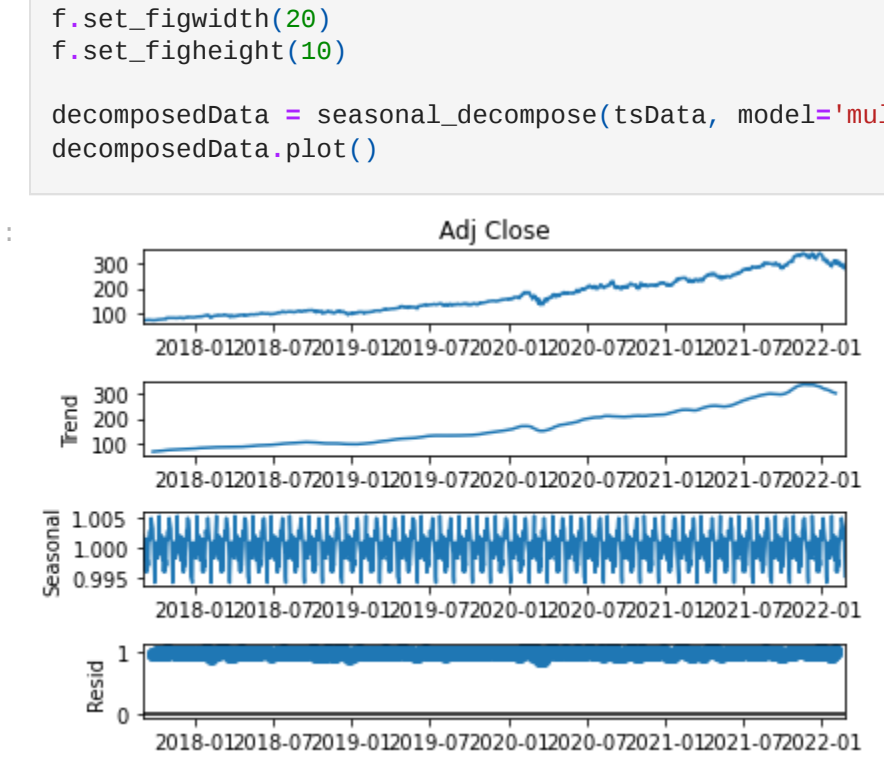
```
(1129,)
Out[ ]: <AxesSubplot:xlabel='Date'>
```



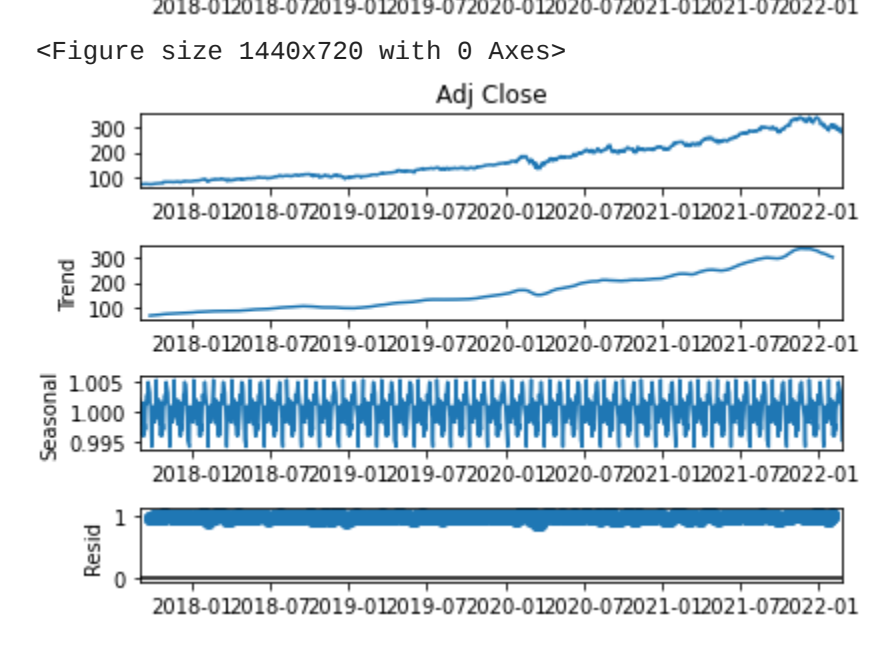
Seasonal Decompotion to obtain trend

```
In [ ]:
from statsmodels.tsa.seasonal import seasonal_decompose
import matplotlib.pyplot as plt

f = plt.figure()
f.set_figwidth(20)
f.set_figheight(10)

decomposedData = seasonal_decompose(tsData, model='multiplicative', period=30)
decomposedData.plot()
```

Out[ ]:

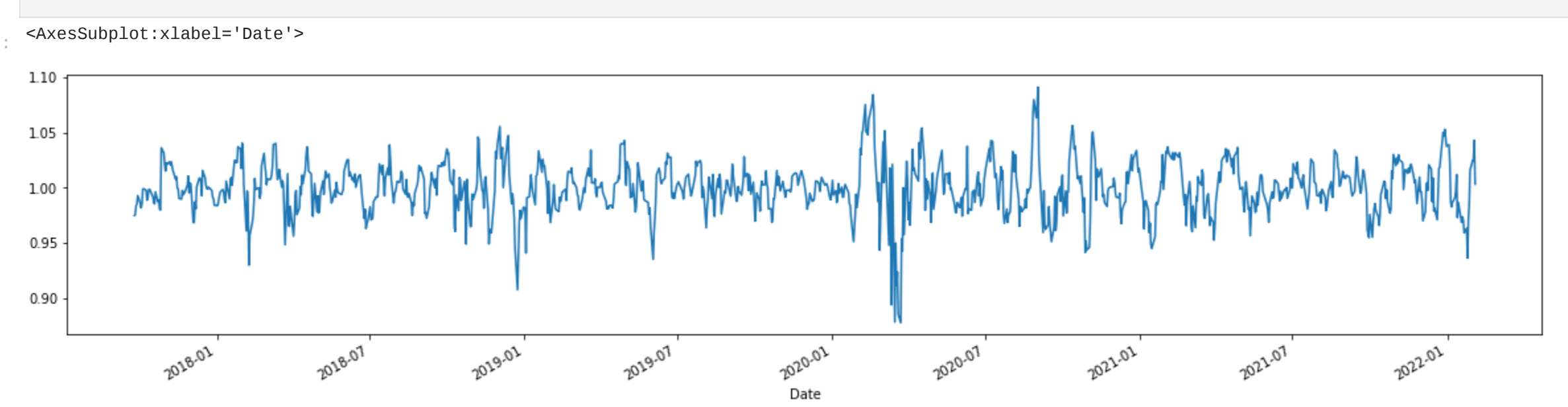



```
<Figure size 1440x720 with 0 Axes>
```



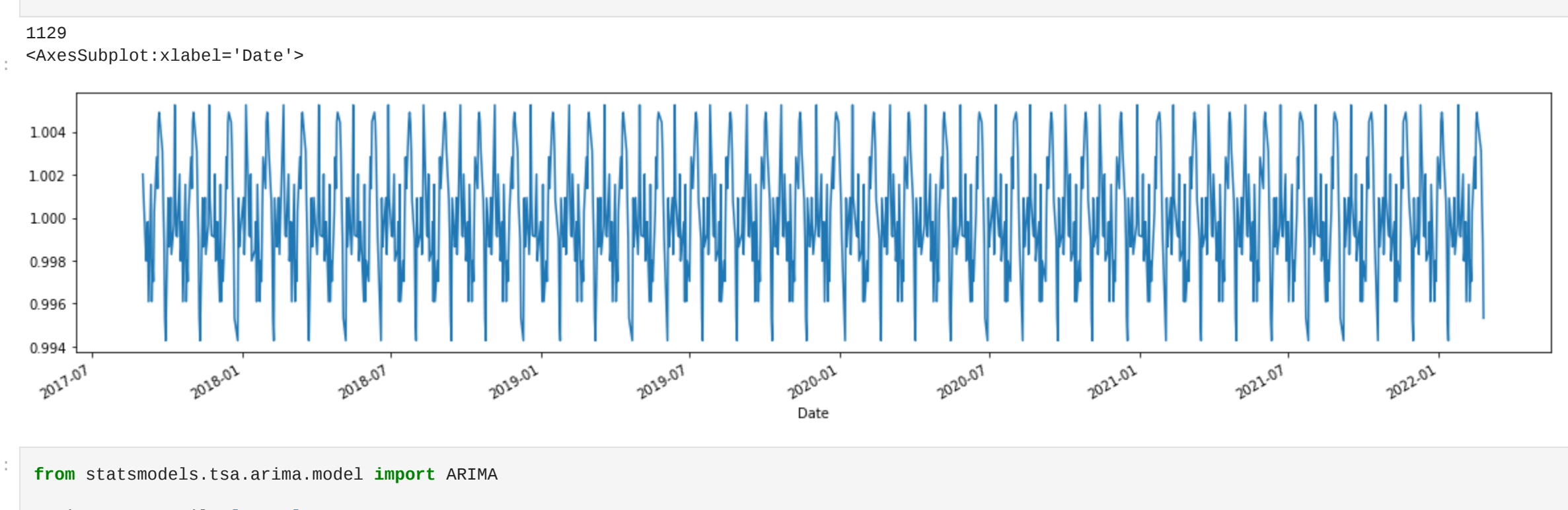

```
In [ ]:
f = plt.figure()
f.set_figwidth(20)
f.set_figheight(4)
decomposedData.resid.plot()
```

```
Out[ ]: <AxesSubplot:xlabel='Date'>
```




```
In [ ]:
f = plt.figure()
f.set_figwidth(20)
f.set_figheight(4)
print(decomposedData.seasonal.size)
decomposedData.seasonal.plot()
```

```
1129
Out[ ]: <AxesSubplot:xlabel='Date'>
```




```
In [ ]:
from statsmodels.tsa.arima.model import ARIMA

train = tsData.iloc[: -10]
test = tsData.iloc[-10 :]
print(train.shape, test.shape)
print('Training Data', train)
print('Testing Data', test)
```

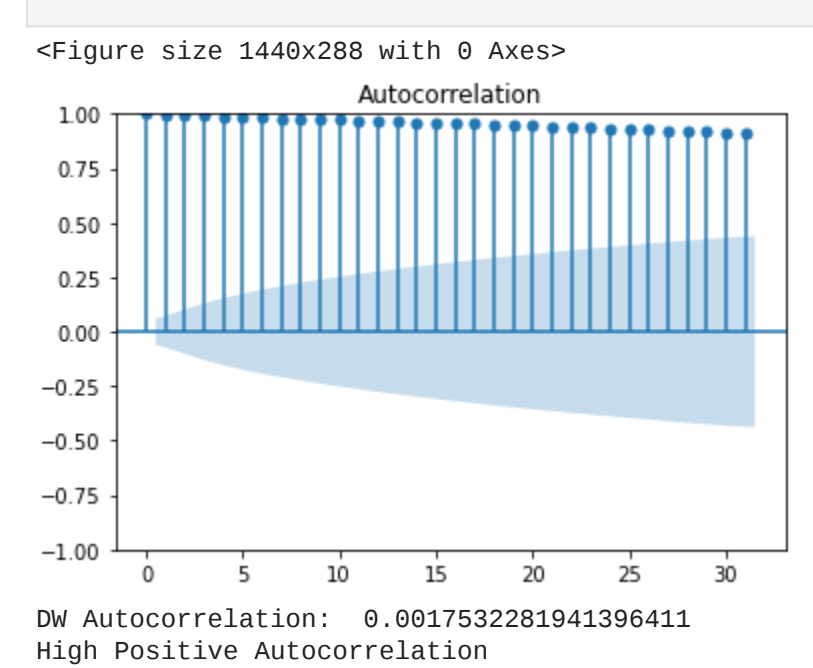
```
(1119,) (10,)
Training Data Date
2017-09-01     69.787331
2017-09-05     69.475868
2017-09-06     69.277672
2017-09-07     70.164894
2017-09-08     69.825096
                 ...
2022-02-04    305.308716
2022-02-07    300.329010
2022-02-08    303.931549
2022-02-09    310.567810
2022-02-10    301.756073
Name: Adj Close, Length: 1119, dtype: float64
Testing Data Date
2022-02-11    294.431213
2022-02-14    294.391296
2022-02-15    299.850006
2022-02-16    299.500000
2022-02-17    290.730011
2022-02-18    287.929993
2022-02-22    287.720001
2022-02-23    280.269989
2022-02-24    294.589996
2022-02-25    297.309998
Name: Adj Close, dtype: float64
```

Autocorrelation Test on MSFT data (Durbin Watson)

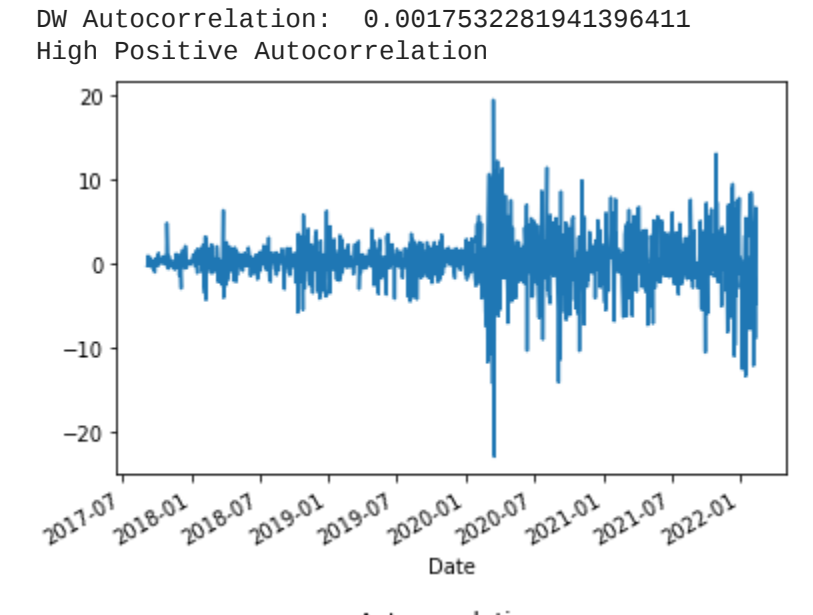
```
In [ ]:
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.stats.stattools import durbin_watson
from statsmodels.regression.linear_model import OLS

def DWtest(data):

    plot_acf(data)
    pyplot.show()

    model1 = sm.OLS(data, np.ones(len(data))).fit()
    autoCorr = durbin_watson(model1.resid)
    print('DW Autocorrelation: ', autoCorr)

    if autoCorr == 2:
        print('No autocorrelation')
    elif autoCorr > 1.5 and autoCorr < 2:
        print('Low Positive autocorrelation')
    elif autoCorr >= 0 and autoCorr <= 1.5:
        print('High Positive Autocorrelation')
    elif autoCorr > 2 and autoCorr < 2.5:
        print('Low Negative autocorrelation')
    elif autoCorr >= 2.5 and autoCorr < 4:
        print('High Negative Autocorrelation')
```

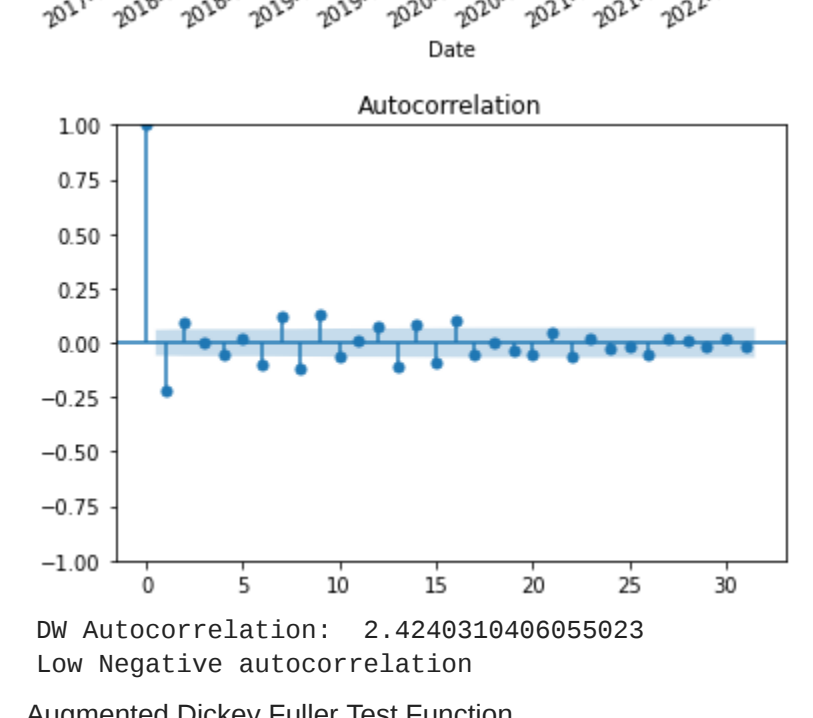
```
In [ ]:
f = plt.figure()
f.set_figwidth(20)
f.set_figheight(4)

DWtest(train)

diff_tsData = train.diff()
diff_tsData = diff_tsData.dropna()
diff_tsData.plot()

DWtest(diff_tsData)
```

```
<Figure size 1440x288 with 0 Axes>
```




```
DW Autocorrelation:  0.0017532281941396411
High Positive Autocorrelation
```






```
DW Autocorrelation:  2.4240310406055023
Low Negative autocorrelation
```

Augmented Dickey Fuller Test Function

```
In [ ]:
from statsmodels.tsa.stattools import adfuller

def ADF_test(data):
    ST = adfuller(data, autolag = 'AIC')
    print('ADF: ', ST[0])
    print('P-value: ', ST[1])
    print('No. of Lags: ', ST[2])
    print('No. of observations used: ', ST[3])
    print('Critical Values: ')
    for item, value in ST[4].items():
        print('\t', item, ': ', value)

    return ST[1]
```

Stationarity Test (ADF)

```
In [ ]:
print('ADF Test for dataset\n')
Stationarity_res = ADF_test(train)

if Stationarity_res > 0.05 :
    print('\nThe given dataset does not reject H0 hypothesis, hence is non-stationary.')
else:
    print('\nThe given dataset rejects H0 hypothesis, hence is stationary.')
```

```
ADF Test for dataset

ADF:  0.07391596920242587
P-value:  0.9642344271450396
No. of Lags:  13
No. of observations used:  1105
Critical Values:
         1% :  -3.4362817248910282
         5% :  -2.8641591533631945
         10% :  -2.5681645177207675

The given dataset does not reject H0 hypothesis, hence is non-stationary.
```

```
In [ ]:
print('ADF Test for differenced dataset\n')
Stationarity_res = ADF_test(diff_tsData)

if Stationarity_res > 0.05 :
    print('\nThe given dataset does not reject H0 hypothesis, hence is non-stationary.')
else:
    print('\nThe given dataset rejects H0 hypothesis, hence is stationary.')
```

```
ADF Test for differenced dataset

ADF:  -9.394264061485925
P-value:  6.437281480420823e-16
No. of Lags:  12
No. of observations used:  1105
Critical Values:
         1% :  -3.4362817248910282
         5% :  -2.8641591533631945
         10% :  -2.5681645177207675

The given dataset rejects H0 hypothesis, hence is stationary.
```

Obtain parameters of ARIMA model

```
In [ ]:
from pmdarima import auto_arima
import warnings
warnings.filterwarnings('ignore')

AIC_result = auto_arima(train, trace=True, suppress_warnings=True, seasonal=True, max_order=(3,3,3))
AIC_result.summary()
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=5715.356, Time=0.64 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=5765.595, Time=0.02 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=5714.023, Time=0.06 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=5720.728, Time=0.09 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=5768.336, Time=0.03 sec
 ARIMA(2,1,0)(0,0,0)[0] intercept   : AIC=5713.520, Time=0.10 sec
 ARIMA(3,1,0)(0,0,0)[0] intercept   : AIC=5714.353, Time=0.11 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=5715.181, Time=0.33 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=5714.235, Time=0.17 sec
 ARIMA(3,1,1)(0,0,0)[0] intercept   : AIC=5703.228, Time=0.54 sec
 ARIMA(4,1,1)(0,0,0)[0] intercept   : AIC=5714.020, Time=0.55 sec
 ARIMA(3,1,2)(0,0,0)[0] intercept   : AIC=5681.721, Time=0.78 sec
 ARIMA(4,1,2)(0,0,0)[0] intercept   : AIC=5702.175, Time=1.44 sec
 ARIMA(3,1,3)(0,0,0)[0] intercept   : AIC=5713.482, Time=1.49 sec
 ARIMA(2,1,3)(0,0,0)[0] intercept   : AIC=5713.543, Time=0.92 sec
 ARIMA(4,1,3)(0,0,0)[0] intercept   : AIC=5706.418, Time=1.14 sec
 ARIMA(3,1,2)(0,0,0)[0]             : AIC=5686.595, Time=0.40 sec

Best model:  ARIMA(3,1,2)(0,0,0)[0] intercept
Total fit time: 8.804 seconds
```

Out[ ]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	1119
Model:	SARIMAX(3, 1, 2)	**Log Likelihood**	-2833.861
Date:	Tue, 01 Mar 2022	**AIC**	5681.721
Time:	00:24:06	**BIC**	5716.856
Sample:	0	**HQIC**	5695.003
	- 1119		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	0.8317	0.322	2.585	0.010	0.201	1.462
ar.L1	-1.8373	0.053	-34.487	0.000	-1.942	-1.733
ar.L2	-1.0561	0.074	-14.247	0.000	-1.201	-0.911
ar.L3	-0.0800	0.029	-2.794	0.005	-0.136	-0.024
ma.L1	1.6606	0.048	34.586	0.000	1.567	1.755
ma.L2	0.7978	0.047	16.866	0.000	0.705	0.890
sigma2	9.3123	0.228	40.768	0.000	8.865	9.760

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	1060.58
Prob(Q):	0.99	**Prob(JB):**	0.00
Heteroskedasticity (H):	6.55	**Skew:**	-0.47
Prob(H) (two-sided):	0.00	**Kurtosis:**	7.68

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

Model ARIMA(3,1,2)

Training of ARIMA Model

```
In [ ]:
model = ARIMA(train, order=(3,1,2))
result = model.fit()
result.summary()
```

Out[ ]:

SARIMAX Results

Dep. Variable:	Adj Close	**No. Observations:**	1119
Model:	ARIMA(3, 1, 2)	**Log Likelihood**	-2837.297
Date:	Tue, 01 Mar 2022	**AIC**	5686.595
Time:	00:24:06	**BIC**	5716.710
Sample:	0	**HQIC**	5697.978
	- 1119		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-1.8264	0.053	-34.565	0.000	-1.930	-1.723
ar.L2	-1.0399	0.074	-14.131	0.000	-1.184	-0.896
ar.L3	-0.0718	0.028	-2.532	0.011	-0.127	-0.016
ma.L1	1.6558	0.048	34.702	0.000	1.562	1.749
ma.L2	0.7954	0.047	16.835	0.000	0.703	0.888
sigma2	9.3697	0.230	40.820	0.000	8.920	9.820

Ljung-Box (L1) (Q):	0.04	**Jarque-Bera (JB):**	1070.99
Prob(Q):	0.84	**Prob(JB):**	0.00
Heteroskedasticity (H):	6.56	**Skew:**	-0.47
Prob(H) (two-sided):	0.00	**Kurtosis:**	7.70

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

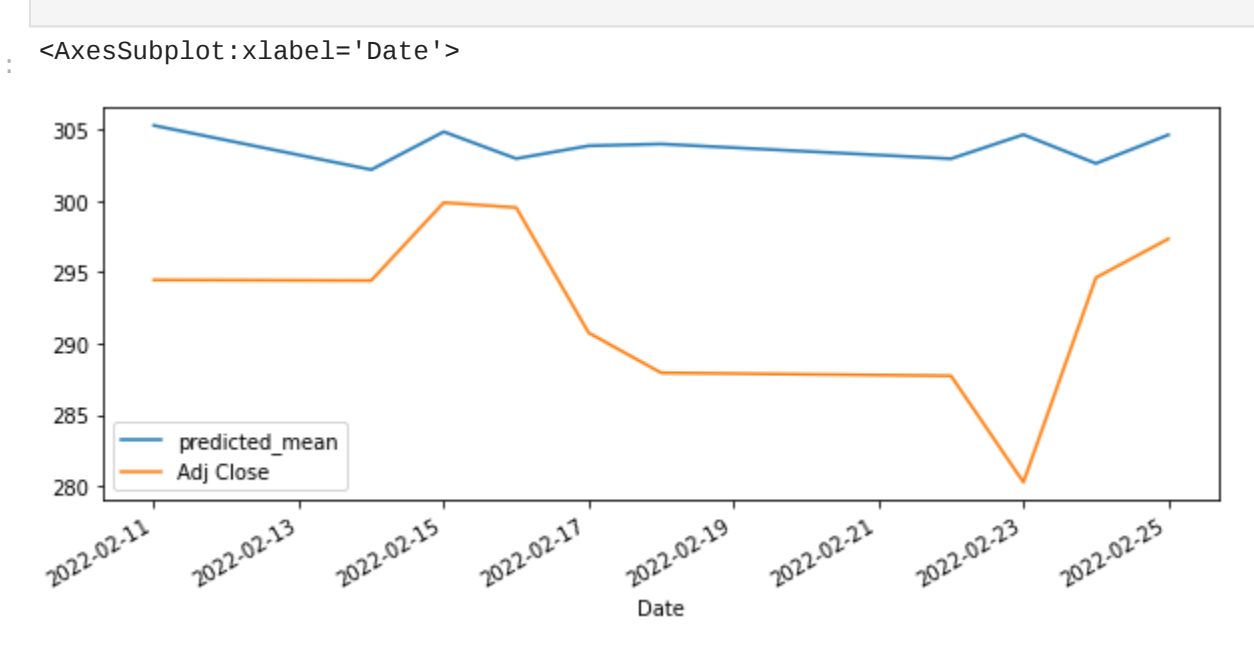
Testing of ARIMA Model

```
In [ ]:
start = len(train)
end = len(train) + len(test) - 1
predictions = result.predict(start=start, end=end)
predictions.index = test.index
for num in range(len(predictions)):
    print('Pred: ', predictions[num], ' Actual: ', test[num])
```

```
Pred:  305.247789633383  Actual:  294.431213
Pred:  302.15183108237693  Actual:  294.391296
Pred:  304.8075785827565  Actual:  299.850006
Pred:  302.9260364284111  Actual:  299.5
Pred:  303.8229490618605  Actual:  290.730011
Pred:  303.9508563012856  Actual:  287.929993
Pred:  302.91957641036424  Actual:  287.720001
Pred:  304.60572527410966  Actual:  280.269989
Pred:  302.5893966012313  Actual:  294.589996
Pred:  304.59259705225435  Actual:  297.309998
```

```
In [ ]:
f = plt.figure()
f.set_figwidth(10)

predictions.plot(legend=True)
test.plot(legend=True)
```

```
Out[ ]: <AxesSubplot:xlabel='Date'>
```




```
In [ ]:
from sklearn.metrics import mean_squared_error
from math import sqrt

mean_test = test.mean()
sq_mse = sqrt(mean_squared_error(predictions, test))
print('Mean: ', mean_test, ' and MSE: ', sq_mse)
print('Percentage error: ', 100*sq_mse/mean_test)
```

```
Mean:  292.6722503000001  and MSE:  12.5774178031748
Percentage error:  4.2974411787528455
```

```
In [ ]:
residuals = predictions - test
f = plt.figure()
f.set_figwidth(10)

residuals.plot(legend=True)
```

```
Out[ ]: <AxesSubplot:xlabel='Date'>
```