CIND820 Initial Coding

November 17, 2020

[5]:
```python
import os
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
from pylab import rcParams
rcParams['figure.figsize'] = 10, 6
from datetime import datetime
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.arima_model import ARIMA
from sklearn.metrics import mean_squared_error, mean_absolute_error
import math
from statsmodels.tsa.stattools import acf, pacf
```

[4]:
```python
pip install pmdarima
```

```
Collecting pmdarima
  Using cached pmdarima-1.7.1-cp37-cp37m-manylinux1_x86_64.whl (1.5 MB)
Requirement already satisfied: scikit-learn>=0.22 in
/opt/conda/lib/python3.7/site-packages (from pmdarima) (0.22.2.post1)
Requirement already satisfied: numpy>=1.17.3 in /opt/conda/lib/python3.7/site-
packages (from pmdarima) (1.18.4)
Requirement already satisfied: setuptools<50.0.0 in
/opt/conda/lib/python3.7/site-packages (from pmdarima) (46.1.3.post20200325)
Requirement already satisfied: pandas>=0.19 in /opt/conda/lib/python3.7/site-
packages (from pmdarima) (1.0.3)
Requirement already satisfied: urllib3 in /opt/conda/lib/python3.7/site-packages
(from pmdarima) (1.25.9)
Requirement already satisfied: scipy>=1.3.2 in /opt/conda/lib/python3.7/site-
packages (from pmdarima) (1.4.1)
Collecting Cython<0.29.18,>=0.29
  Using cached Cython-0.29.17-cp37-cp37m-manylinux1_x86_64.whl (2.1 MB)
Requirement already satisfied: statsmodels<0.12,>=0.11 in
/opt/conda/lib/python3.7/site-packages (from pmdarima) (0.11.1)
Requirement already satisfied: joblib>=0.11 in /opt/conda/lib/python3.7/site-
```

```
packages (from pmdarima) (0.15.1)
Requirement already satisfied: pytz>=2017.2 in /opt/conda/lib/python3.7/site-
packages (from pandas>=0.19->pmdarima) (2020.1)
Requirement already satisfied: python-dateutil>=2.6.1 in
/opt/conda/lib/python3.7/site-packages (from pandas>=0.19->pmdarima) (2.8.1)
Requirement already satisfied: patsy>=0.5 in /opt/conda/lib/python3.7/site-
packages (from statsmodels<0.12,>=0.11->pmdarima) (0.5.1)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.7/site-
packages (from python-dateutil>=2.6.1->pandas>=0.19->pmdarima) (1.14.0)
Installing collected packages: Cython, pmdarima
  Attempting uninstall: Cython
    Found existing installation: Cython 0.29.19
    Uninstalling Cython-0.29.19:
      Successfully uninstalled Cython-0.29.19
Successfully installed Cython-0.29.17 pmdarima-1.7.1
Note: you may need to restart the kernel to use updated packages.
```

[6]:
```
from pmdarima.arima import auto_arima
```

[7]:
```
#import NASDAQ data
df=pd.read_csv("IXIC_v1.csv", sep=",")
```

[8]:
```
#understand data format and clean up data
from datetime import datetime
con=df['Date']
df['Date']=pd.to_datetime(df['Date'])
df.set_index('Date', inplace=True)
#check datatype of index
df.index
```

[8]:
```
DatetimeIndex(['2010-01-04', '2010-01-05', '2010-01-06', '2010-01-07',
               '2010-01-08', '2010-01-11', '2010-01-12', '2010-01-13',
               '2010-01-14', '2010-01-15',
               …
               '2020-09-17', '2020-09-18', '2020-09-21', '2020-09-22',
               '2020-09-23', '2020-09-24', '2020-09-25', '2020-09-28',
               '2020-09-29', '2020-09-30'],
              dtype='datetime64[ns]', name='Date', length=2705, freq=None)
```

[9]:
```
df['year'] = df.index.year
df['month'] = df.index.month
df['day'] = df.index.day
```

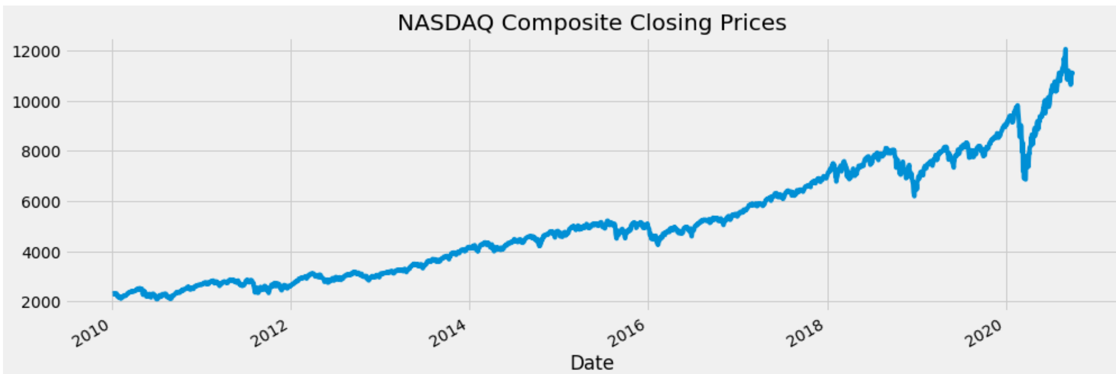
[10]:
```
df.sample(5, random_state=0)
```

[10]:
```
                  Close  year  month  day
Date
```

```
2010-05-17  2354.229980  2010      5   17
2018-02-01  7385.859863  2018      2    1
2013-07-29  3599.139893  2013      7   29
2016-11-08  5193.490234  2016     11    8
2014-06-13  4310.649902  2014      6   13
```

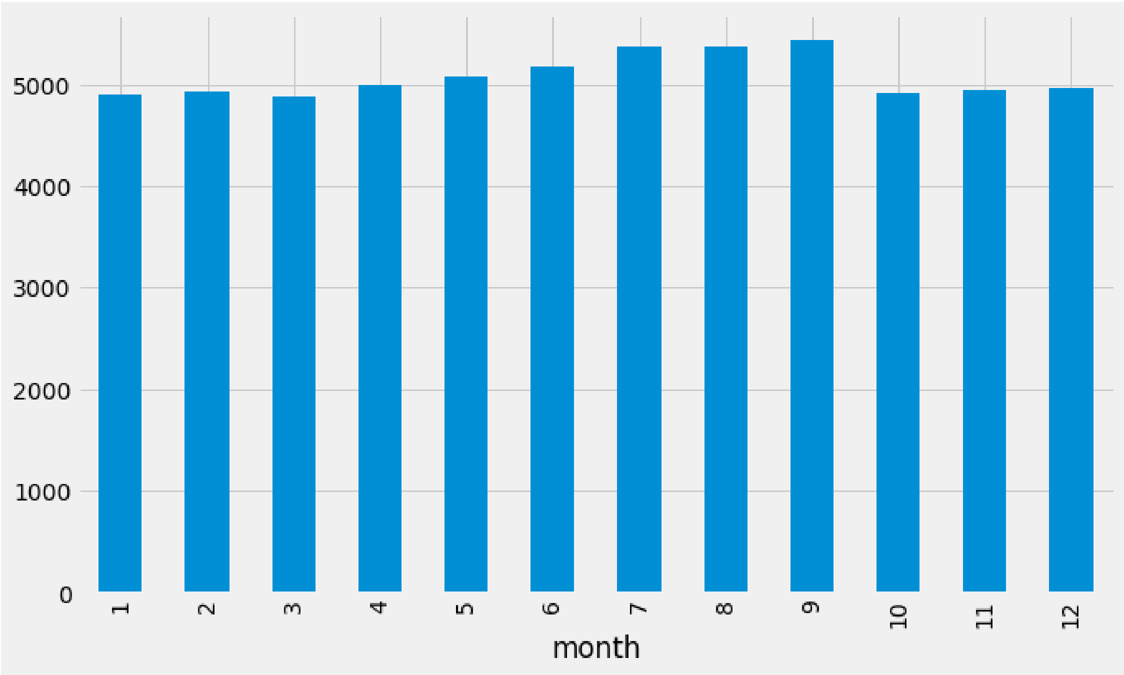
[11]:
```
#plot NASDAQ trend
temp=df.groupby(['Date'])['Close'].mean()
temp.plot(figsize=(15,5), title= 'NASDAQ Composite Closing Prices', fontsize=14)
```

[11]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9f03551210>



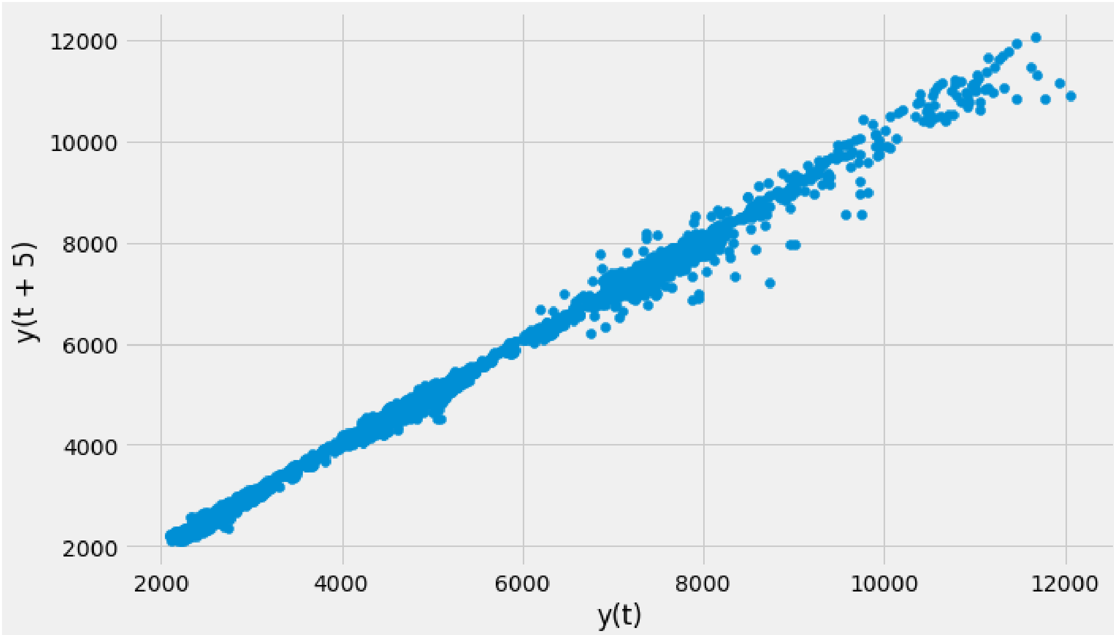
[12]:
```
df.groupby('month')['Close'].mean().plot.bar()
#on average, september has the highest average price compares to the other␣
↪months.
```

[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9f034c8b50>



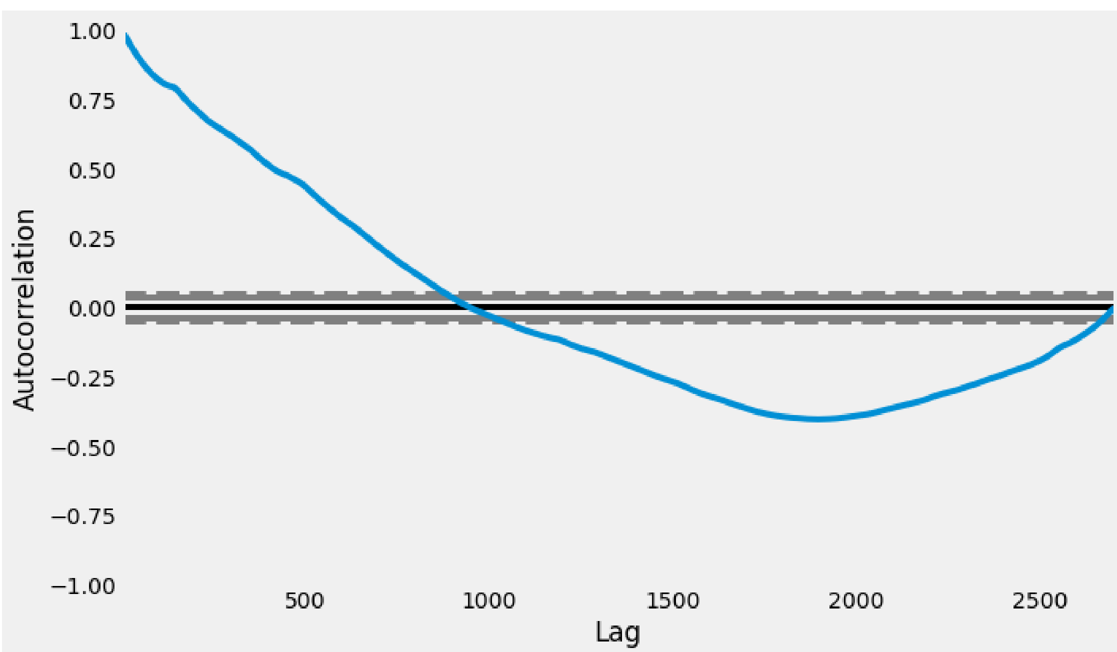

```
[13]: #lag plot
      from pandas.plotting import lag_plot
      lag_plot(df['Close'],lag=5)

      #Graph shows a linear pattern. Implies data points are non random and suggests␣
       ↪that an autoregressive model might be appropriate.
```

```
[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9f0333a690>
```



[14]:
```
from pandas.plotting import autocorrelation_plot
autocorrelation_plot(df['Close'])
#there is high level of correlation
```

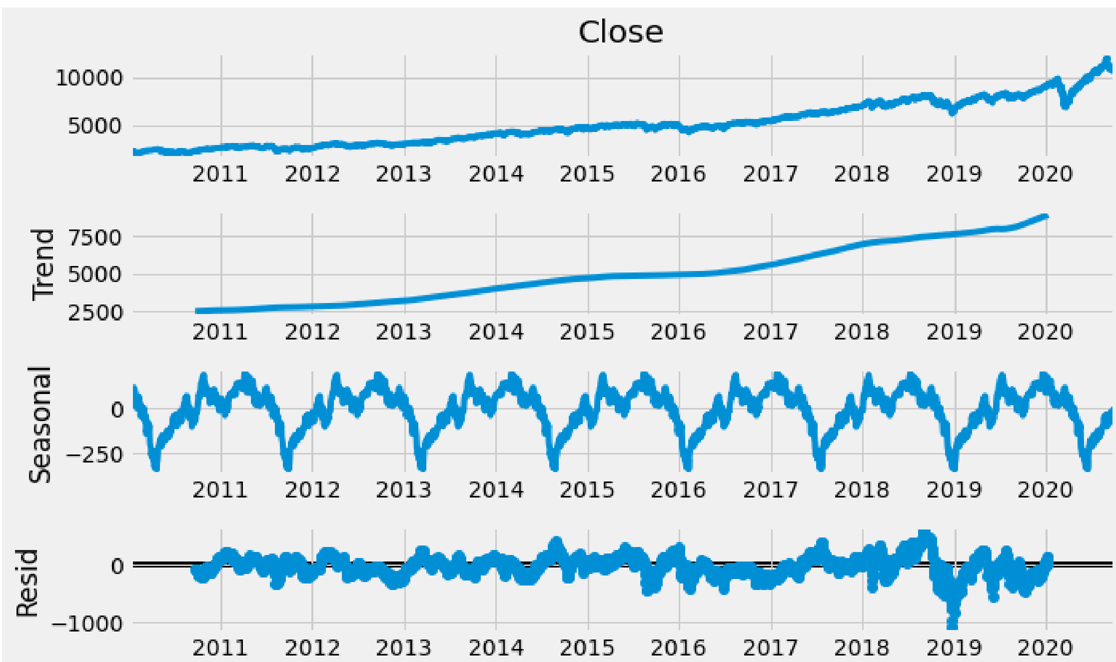
[14]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9f0325c710>



[15]:
```
#data is not stationary based on high p value
from statsmodels.tsa.stattools import adfuller
result = adfuller(df.Close.dropna())
print(f"ADF Statstic: {result[0]}")
print(f"p-value:{result[1]}")
```

```
ADF Statstic: 1.4430465972942679
p-value:0.9973011850493003
```

[16]:
```
#decompose data
import statsmodels.api as sm
res = sm.tsa.seasonal_decompose(df['Close'],model= 'addictive',period = 365)
resplot = res.plot()
#data shows upward trend and presents seasonlity
```



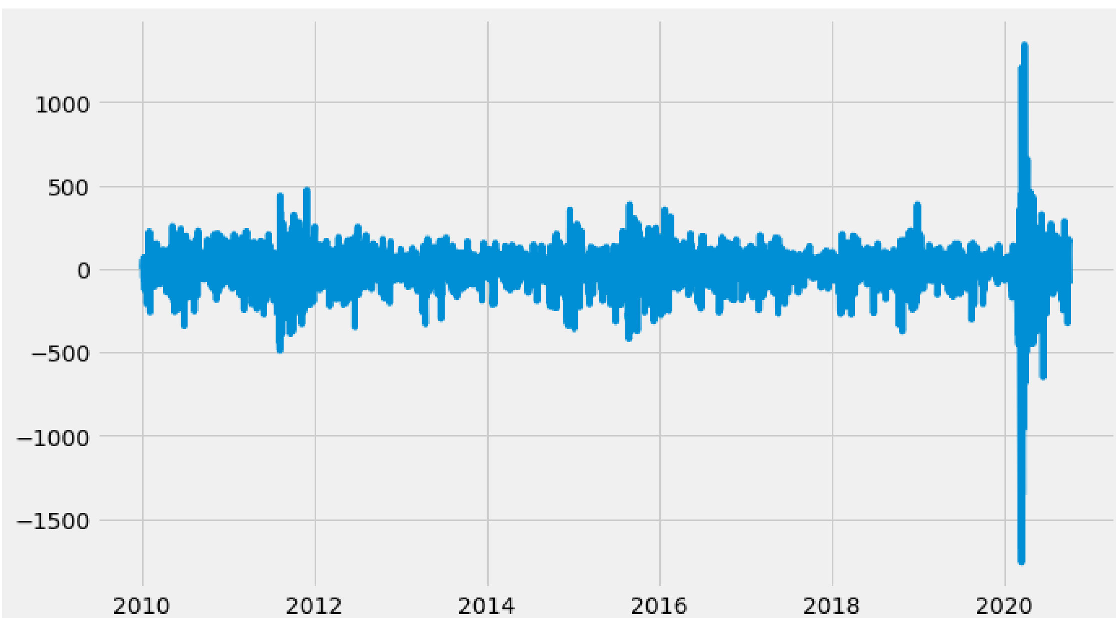
[97]:
```
def plot_df(df,x,y,title= "", xlabel = "Date", ylabel='Value',dpi=100):
    plt.plot(x,y)
    plt.show()
```

[98]:
```
#apply log transformation to stablize data
plt.plot(df.apply(np.log)['Close'])
```

[98]: `[<matplotlib.lines.Line2D at 0x7f9e5808b950>]`

[96]:
```
#To covert data into stationary dataset, first differencing has to be applied.␣
 ↪With first differencing, empty field needs to be filled as 0.
plt.plot(df['Close'].diff(1).fillna(0))
```

[96]: [<matplotlib.lines.Line2D at 0x7f9e58131f90>]



[20]:
```
#confirm stationarity
from statsmodels.tsa.stattools import adfuller
result = adfuller(np.log(df['Close']).diff(1).fillna(0))
print(f"ADF Statstic: {result[0]}")
print(f"p-value:{result[1]}")
```

```
ADF Statstic: -11.770291597674845
p-value:1.0940406662618215e-21
```

[21]:
```
df_st= df.diff(1).fillna(0)
```

[22]:
```
#understand the structure of the stationary dataset
df_st.head()
```

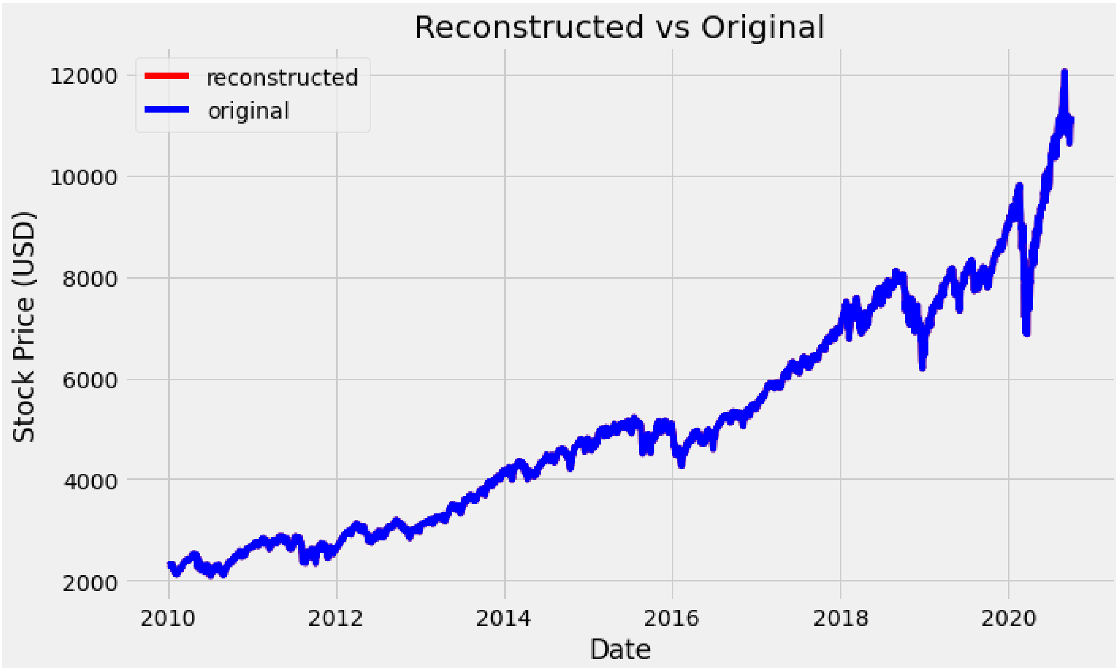
[22]:

Date	Close	year	month	day
2010-01-04	0.000000	0.0	0.0	0.0
2010-01-05	0.290039	0.0	0.0	1.0
2010-01-06	-7.619873	0.0	0.0	1.0
2010-01-07	-1.040039	0.0	0.0	1.0
2010-01-08	17.119873	0.0	0.0	1.0

[23]:
```
#With transformation to maintain stationarity, we need to be model back to the␣
↪original dataset in order to predict stock price.
df_reconstruct=df_st.copy()
df_resconstruct=df_reconstruct.cumsum()
```

[24]:
```
df_reconstruct=df_st.copy()
df_reconstruct.iloc[0,:]=df.iloc[0,:]
df_reconstruct = df_reconstruct.cumsum()
```

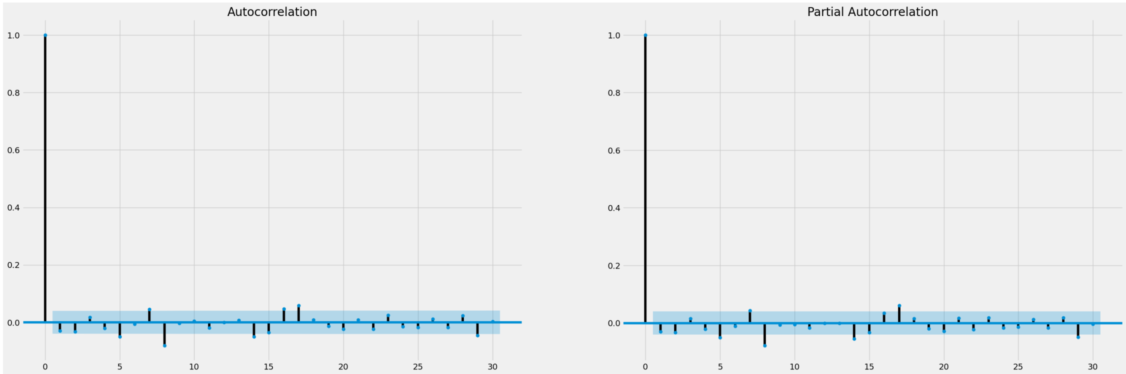
[25]:
```
plt.plot(df.index, df_reconstruct['Close'], 'r-',  label='reconstructed')
plt.plot(df.index, df['Close'], 'b-', label = 'original')
plt.xlabel('Date'); plt.ylabel('Stock Price (USD)')
plt.title('Reconstructed vs Original')
plt.legend();
#plot confirms the same pattern of data
```



[26]:
```
#define data
class TimeSeriesData():
    def __init__(self, df):
        self.data = df
        self.stationary = self.stationarize(df)
        self.reconstructed = self.reconstruct(self.stationary, self.data)

    def reconstruct(self, st, org):
        x = st.copy()
        x.iloc[0,:] = org.iloc[0,:]
        return x.cumsum()

    def stationarize(self, data):
        return data.diff(1).fillna(0)
```

[27]:
```
#split dataset
x_train = TimeSeriesData(df[:int((len(df)*0.9))])
x_valid = TimeSeriesData(df[int((len(df)*0.9)):])
```

[28]:
```
#plot ACF and PACF for the stationary dataset
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
fig, axes = plt.subplots(1,2,figsize=(30,10), dpi= 100)
plot_acf(x_train.stationary['Close'].values.tolist(), lags=30, ax=axes[0]);
plot_pacf(x_train.stationary['Close'].values.tolist(), lags=30, ax=axes[1]);
```



[29]:
```
#using auto_arima to aquire p and q value with min AIC.
from pmdarima import auto_arima
model = auto_arima(x_train.data['Close'], trace=True, error_action='ignore',␣
 ↪suppress_warnings=True)
model.fit(x_train.data['Close'])
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=26066.202, Time=2.11 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=26076.884, Time=0.06 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=26076.691, Time=0.12 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=26076.549, Time=0.17 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=26079.882, Time=0.03 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=26075.487, Time=2.17 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=26075.648, Time=1.86 sec
 ARIMA(3,1,2)(0,0,0)[0] intercept   : AIC=26068.264, Time=3.18 sec
 ARIMA(2,1,3)(0,0,0)[0] intercept   : AIC=26068.512, Time=2.98 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=26070.891, Time=1.45 sec
 ARIMA(1,1,3)(0,0,0)[0] intercept   : AIC=26079.396, Time=1.73 sec
 ARIMA(3,1,1)(0,0,0)[0] intercept   : AIC=26079.243, Time=1.46 sec
 ARIMA(3,1,3)(0,0,0)[0] intercept   : AIC=26065.626, Time=4.68 sec
 ARIMA(4,1,3)(0,0,0)[0] intercept   : AIC=26068.108, Time=4.90 sec
 ARIMA(3,1,4)(0,0,0)[0] intercept   : AIC=26065.348, Time=6.39 sec
 ARIMA(2,1,4)(0,0,0)[0] intercept   : AIC=26067.212, Time=4.68 sec
 ARIMA(4,1,4)(0,0,0)[0] intercept   : AIC=26066.196, Time=10.05 sec
 ARIMA(3,1,5)(0,0,0)[0] intercept   : AIC=26065.247, Time=14.73 sec
 ARIMA(2,1,5)(0,0,0)[0] intercept   : AIC=26067.822, Time=14.77 sec
 ARIMA(4,1,5)(0,0,0)[0] intercept   : AIC=26068.541, Time=16.31 sec
 ARIMA(3,1,5)(0,0,0)[0]             : AIC=26070.298, Time=3.68 sec

Best model:  ARIMA(3,1,5)(0,0,0)[0] intercept
Total fit time: 97.554 seconds
```

[29]:
```
ARIMA(maxiter=50, method='lbfgs', order=(3, 1, 5), out_of_sample_size=0,
      scoring='mse', scoring_args={}, seasonal_order=(0, 0, 0, 0),
```

```
start_params=None, suppress_warnings=True, trend=None,
with_intercept=True)
```

[30]:
```
model_arima = ARIMA(x_train.data['Close'].values, order=(3,1,5))
```

[31]:
```
result_arima = model_arima.fit(disp=-1)
```

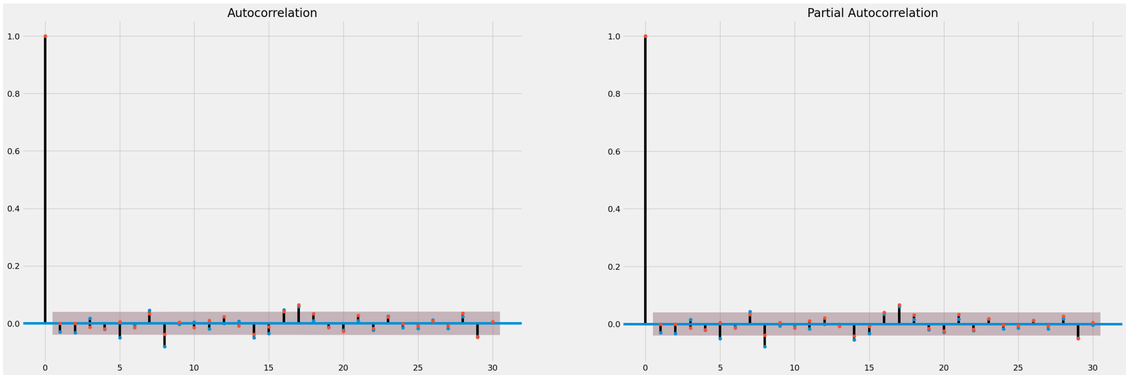
[32]:
```
print(result_arima.summary())
```

```
                             ARIMA Model Results
==============================================================================
Dep. Variable:                    D.y   No. Observations:                 2433
Model:                 ARIMA(3, 1, 5)   Log Likelihood              -13022.009
Method:                       css-mle   S.D. of innovations             51.074
Date:                Mon, 16 Nov 2020   AIC                          26064.018
Time:                        17:52:43   BIC                          26121.986
Sample:                             1   HQIC                         26085.092

==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          2.3632      0.574      4.119      0.000       1.239       3.488
ar.L1.D.y      0.2905      0.093      3.125      0.002       0.108       0.473
ar.L2.D.y     -0.2264      0.079     -2.873      0.004      -0.381      -0.072
ar.L3.D.y      0.8377      0.065     12.920      0.000       0.711       0.965
ma.L1.D.y     -0.3212      0.095     -3.377      0.001      -0.508      -0.135
ma.L2.D.y      0.2058      0.084      2.462      0.014       0.042       0.370
ma.L3.D.y     -0.8151      0.073    -11.125      0.000      -0.959      -0.671
ma.L4.D.y      0.0069      0.027      0.254      0.799      -0.046       0.060
ma.L5.D.y     -0.0224      0.024     -0.948      0.343      -0.069       0.024
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1            1.0402           -0.0000j            1.0402           -0.0000
AR.2           -0.3849           -0.9997j            1.0713           -0.3085
AR.3           -0.3849           +0.9997j            1.0713            0.3085
MA.1            1.0216           -0.0000j            1.0216           -0.0000
MA.2           -0.4009           -1.0266j            1.1021           -0.3092
MA.3           -0.4009           +1.0266j            1.1021            0.3092
MA.4            0.0430           -5.9919j            5.9921           -0.2489
MA.5            0.0430           +5.9919j            5.9921            0.2489
-----------------------------------------------------------------------------
```

[33]:
```
#understand residual
residuals = pd.DataFrame(result_arima.resid)
```

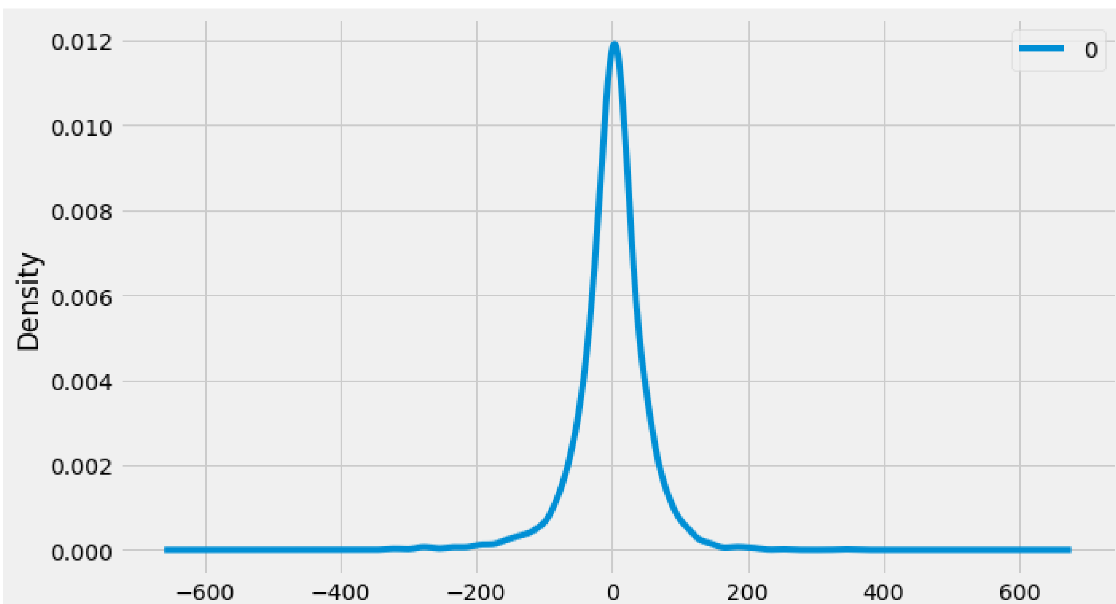
[34]:
```
plot_acf(residuals, lags=30, ax=axes[0])
plot_pacf(residuals, lags=30, ax=axes[1])
```

[34]:

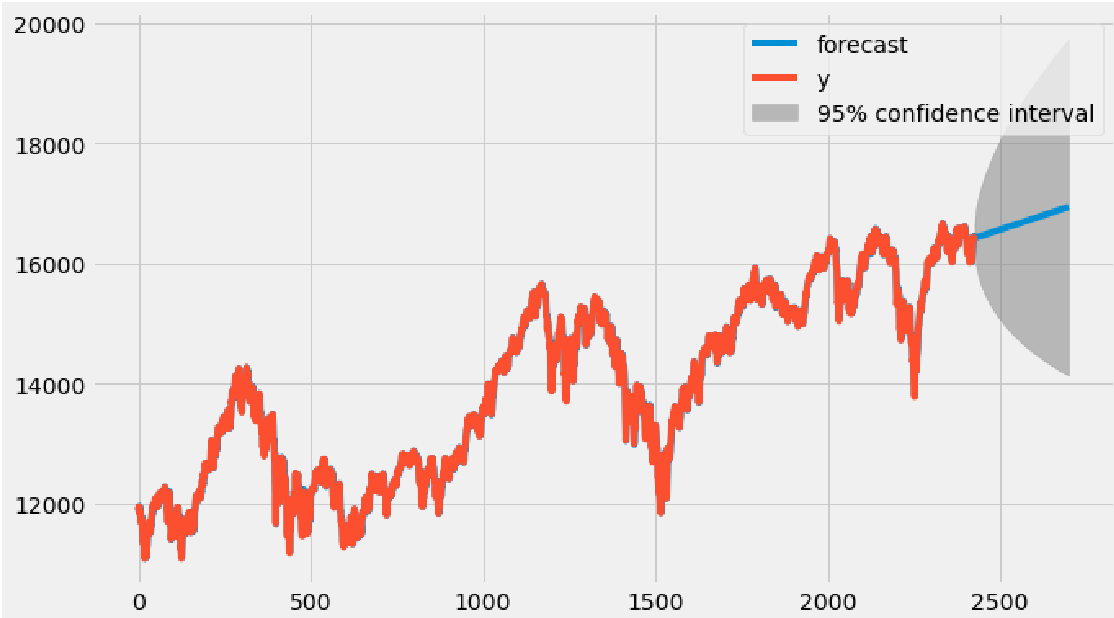


[35]:
```
residuals.plot(kind='kde')
```

[35]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9effa0b3d0>



[122]:
```
result_arima.plot_predict(1,2700);
```



[81]:
```
prediction = result_arima.predict(len(df)-208,len(df)-1)
def rmse(validation, prediction):
    error = validation - prediction
    return np.sqrt(np.mean(error**2))
```

[82]:
```
from statsmodels.tools.eval_measures import rmse
#RMSE for ARIMA Model
err_LSTM = rmse(x_valid.data['Close'], np.append(x_train.data.iloc[-1,:
 ↪]['Close'], prediction).cumsum()[1:])
print('RMSE with LSTM', err_LSTM)
```

```
RMSE with LSTM 1361.2487894244925
```

[ ]:
```

```

[ ]:
```
#same analysis for TSX price
```

[83]:
```
#upload TSX price
df=pd.read_csv("GSPTSE_v1.csv", sep=",")
```

[84]:
```
#understand the data and covert date format
from datetime import datetime
con=df['Date']
df['Date']=pd.to_datetime(df['Date'])
df.set_index('Date', inplace=True)
#check datatype of index
df.index
```

[84]: DatetimeIndex(['2010-01-04', '2010-01-05', '2010-01-06', '2010-01-07',
               '2010-01-08', '2010-01-11', '2010-01-12', '2010-01-13',
               '2010-01-14', '2010-01-15',
               …
               '2020-09-17', '2020-09-18', '2020-09-21', '2020-09-22',
               '2020-09-23', '2020-09-24', '2020-09-25', '2020-09-28',
               '2020-09-29', '2020-09-30'],
              dtype='datetime64[ns]', name='Date', length=2697, freq=None)

[85]:
```
df['year'] = df.index.year
df['month'] = df.index.month
df['day'] = df.index.day
```

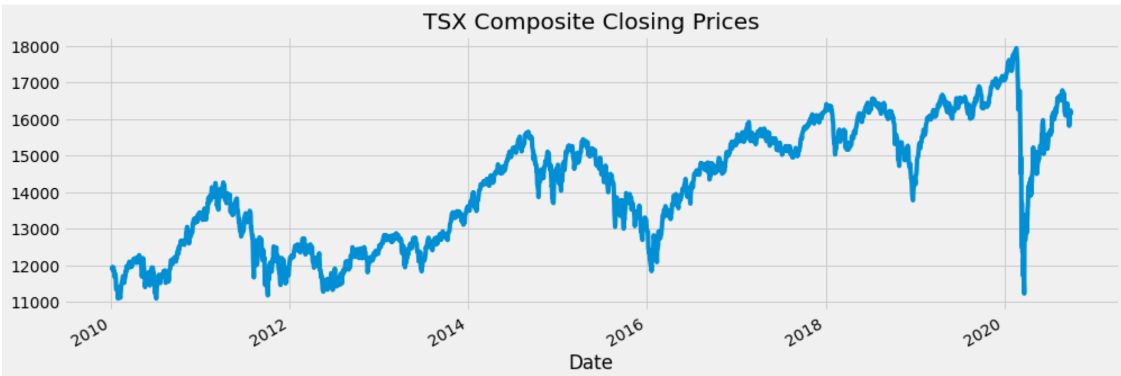
[86]:
```
df.sample(5, random_state=0)
```

[86]:

Date	Close	year	month	day
2012-09-06	12139.70020	2012	9	6
2016-03-04	13212.50000	2016	3	4
2014-09-23	15125.70020	2014	9	23
2017-05-31	15349.90039	2017	5	31
2016-02-16	12555.00000	2016	2	16

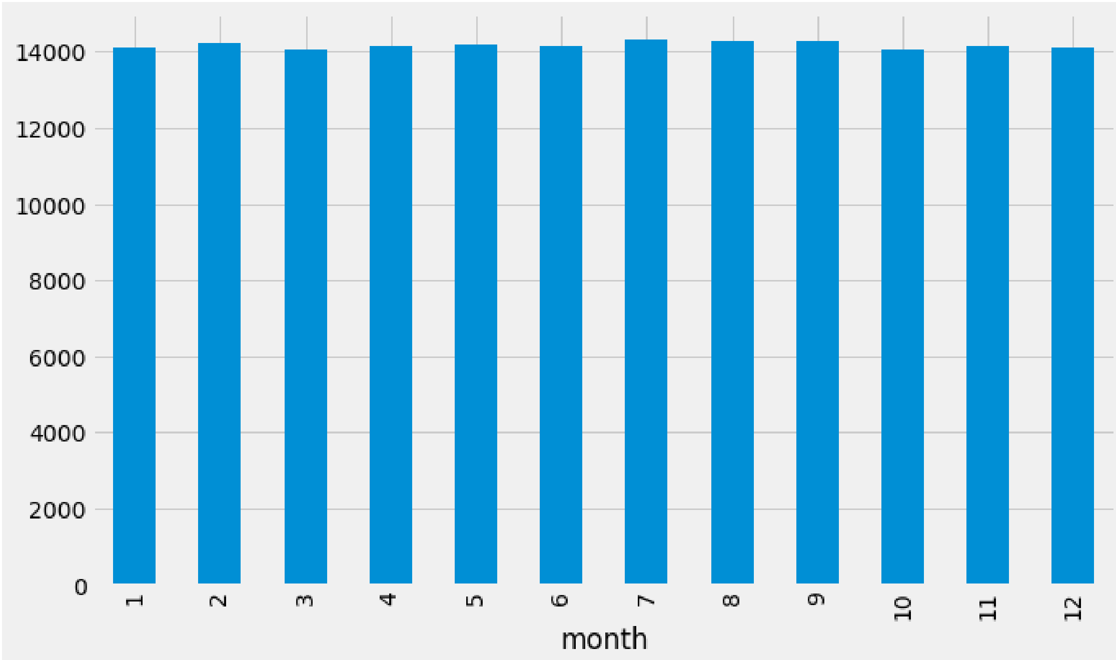
[88]:
```
#plot TSX trend
temp=df.groupby(['Date'])['Close'].mean()
temp.plot(figsize=(15,5), title= 'TSX Composite Closing Prices', fontsize=14)
```

[88]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9e58d0f950>



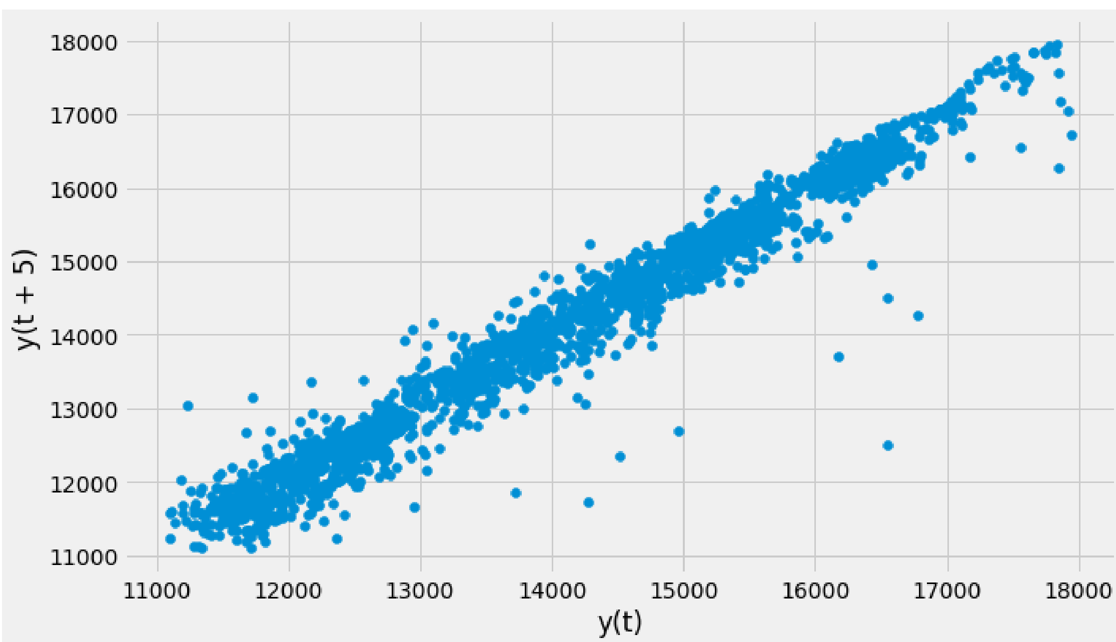
[89]:
```
df.groupby('month')['Close'].mean().plot.bar()
```

[89]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9e903a3410>



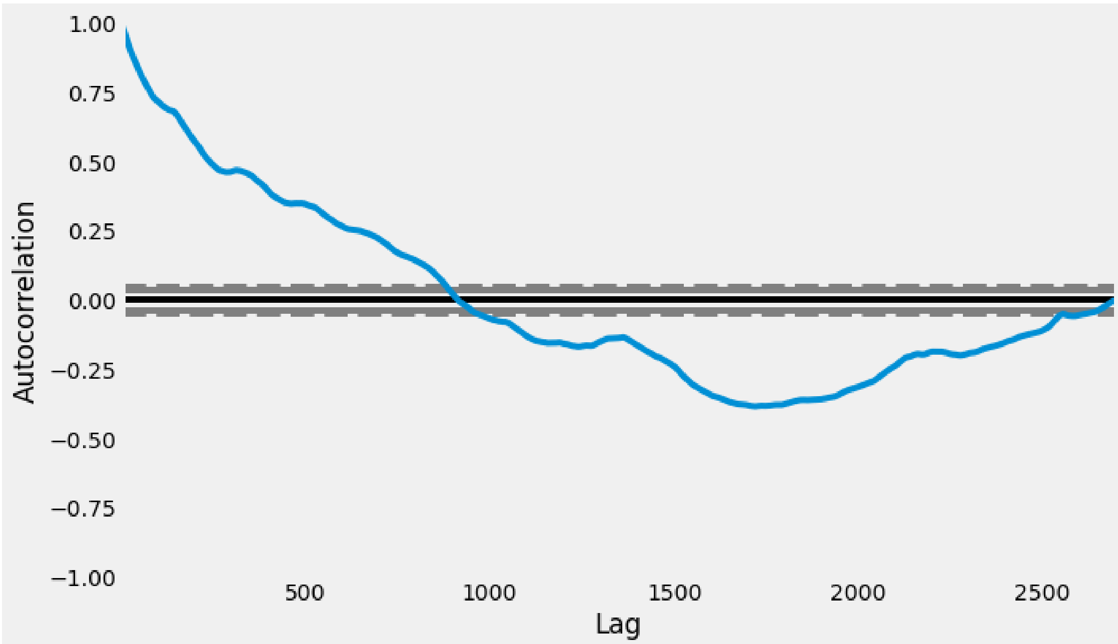
[90]:
```
#lag plot
from pandas.plotting import lag_plot
lag_plot(df['Close'],lag=5)
#a linear plot also indicates non random dataset
```

[90]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9e58c3da90>



[91]:
```
from pandas.plotting import autocorrelation_plot
autocorrelation_plot(df['Close'])
#autocorrelation suggests arima might be a good model
```

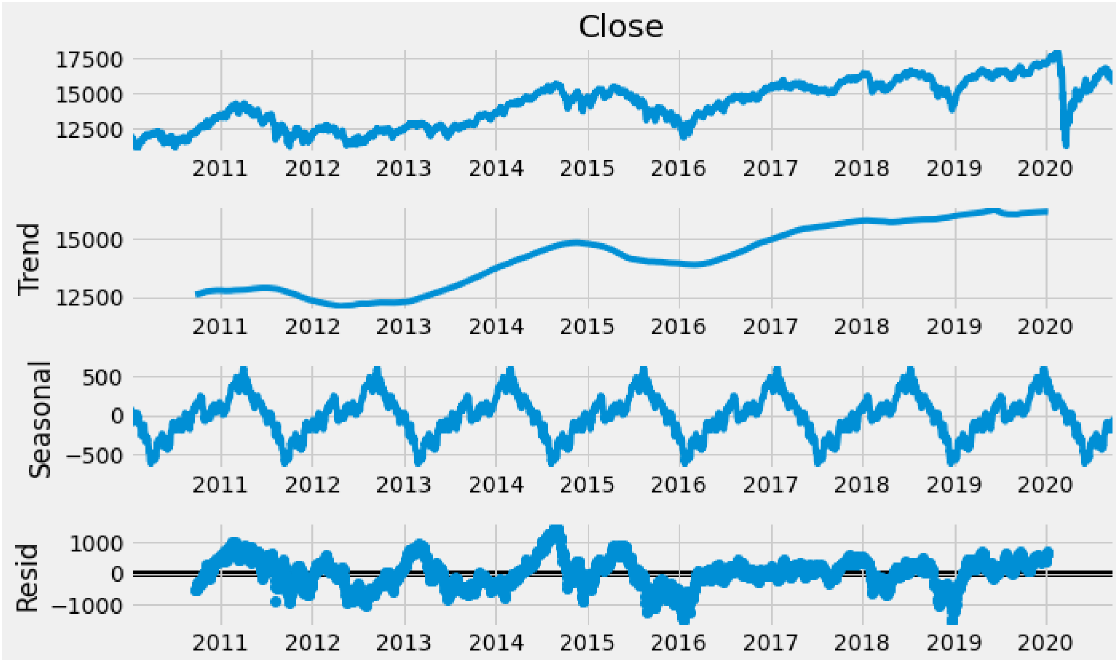
[91]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9e58bf0910>



[92]:
```
#original data shows as not stationary due to high p level
from statsmodels.tsa.stattools import adfuller
result = adfuller(df.Close.dropna())
print(f"ADF Statstic: {result[0]}")
print(f"p-value:{result[1]}")
```

```
ADF Statstic: -2.1272017170757755
p-value:0.23371823999228158
```

[93]:
```
#decompose data
import statsmodels.api as sm
res = sm.tsa.seasonal_decompose(df['Close'],model= 'addictive',period = 365)
resplot = res.plot()
#upward trend
```



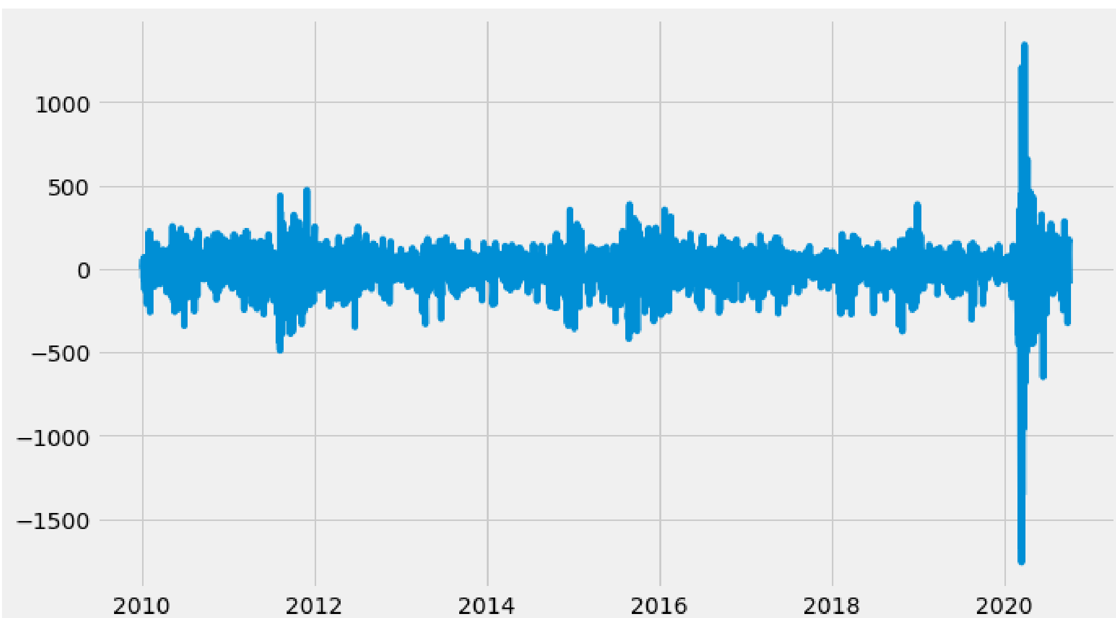
[100]:
```
def plot_df(df,x,y,title= "", xlabel = "Date", ylabel='Value',dpi=100):
    plt.plot(x,y)
    plt.show()
```

[101]:
```
#apply log transformation to stablize data
plt.plot(df.apply(np.log)['Close'])
```

[101]: [<matplotlib.lines.Line2D at 0x7f9e3a7c8290>]

[102]:
```
#To covert data into stationary dataset, first differencing has to be applied.␣
↪With first differencing, empty field needs to be filled as 0.
plt.plot(df['Close'].diff(1).fillna(0))
```

[102]:
```
[<matplotlib.lines.Line2D at 0x7f9e3a7acd10>]
```



[103]:
```
#confirm stationarity
from statsmodels.tsa.stattools import adfuller
result = adfuller(np.log(df['Close']).diff(1).fillna(0))
print(f"ADF Statstic: {result[0]}")
print(f"p-value:{result[1]}")
```

```
ADF Statstic: -10.92108896454532
p-value:1.037610106877016e-19
```

[104]:
```
df_st= df.diff(1).fillna(0)
```

[105]:
```
#understand the structure of the stationary dataset
df_st.head()
```

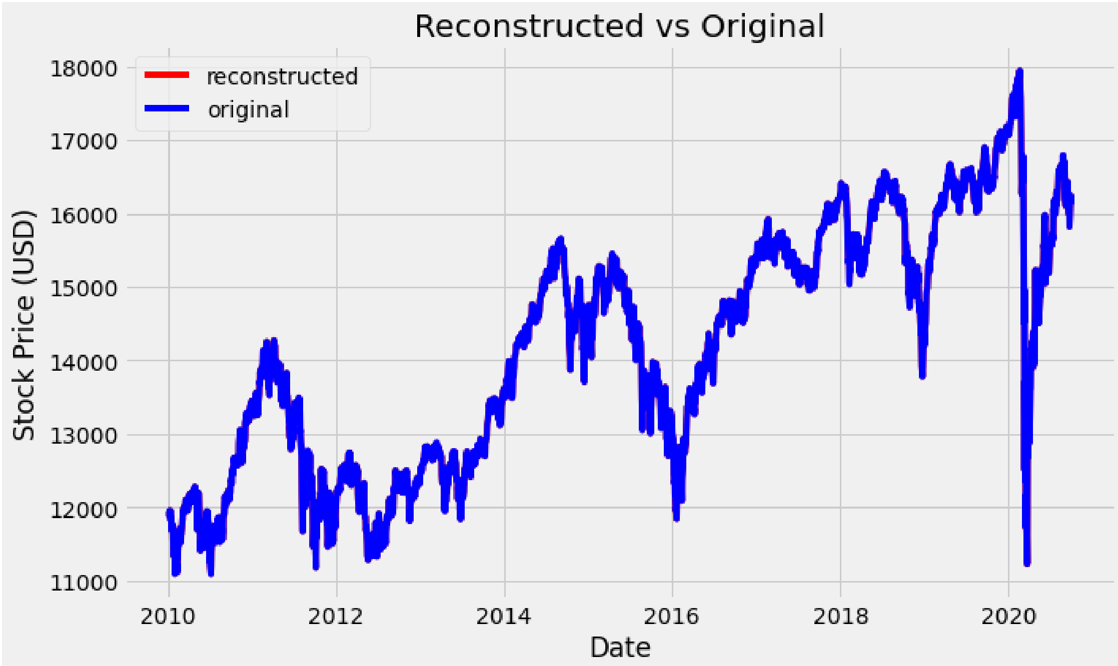
[105]:

Date	Close	year	month	day
2010-01-04	0.00000	0.0	0.0	0.0
2010-01-05	21.19922	0.0	0.0	1.0
2010-01-06	56.40039	0.0	0.0	1.0
2010-01-07	-57.00000	0.0	0.0	1.0
2010-01-08	66.29981	0.0	0.0	1.0

[106]:
```
#With transformation to maintain stationarity, we need to be model back to the␣
↪original dataset in order to predict stock price.
df_reconstruct=df_st.copy()
df_resconstruct=df_reconstruct.cumsum()
```

[107]:
```
df_reconstruct=df_st.copy()
df_reconstruct.iloc[0,:]=df.iloc[0,:]
df_reconstruct = df_reconstruct.cumsum()
```

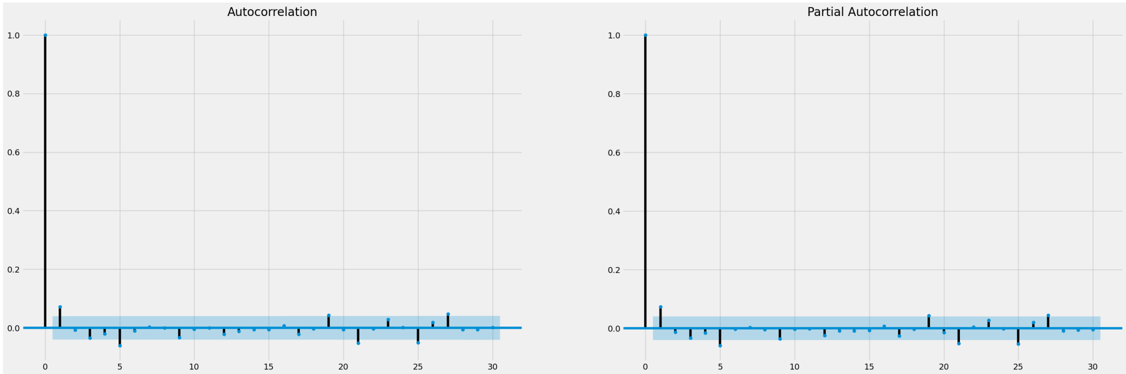
[108]:
```
plt.plot(df.index, df_reconstruct['Close'], 'r-',  label='reconstructed')
plt.plot(df.index, df['Close'], 'b-', label = 'original')
plt.xlabel('Date'); plt.ylabel('Stock Price (USD)')
plt.title('Reconstructed vs Original')
plt.legend();
#plot confirms the same pattern of data
```



[109]:
```
#define data
class TimeSeriesData():
    def __init__(self, df):
        self.data = df
        self.stationary = self.stationarize(df)
        self.reconstructed = self.reconstruct(self.stationary, self.data)

    def reconstruct(self, st, org):
        x = st.copy()
        x.iloc[0,:] = org.iloc[0,:]
        return x.cumsum()

    def stationarize(self, data):
        return data.diff(1).fillna(0)
```

[110]:
```
#split dataset
x_train = TimeSeriesData(df[:int((len(df)*0.9))])
x_valid = TimeSeriesData(df[int((len(df)*0.9)):])
```

[111]:
```
#plot ACF and PACF for the stationary dataset
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
fig, axes = plt.subplots(1,2,figsize=(30,10), dpi= 100)
plot_acf(x_train.stationary['Close'].values.tolist(), lags=30, ax=axes[0]);
plot_pacf(x_train.stationary['Close'].values.tolist(), lags=30, ax=axes[1]);
```



[112]:
```
#using auto_arima to aquire p and q value with min AIC.
from pmdarima import auto_arima
model = auto_arima(x_train.data['Close'], trace=True, error_action='ignore',␣
 ↪suppress_warnings=True)
model.fit(x_train.data['Close'])
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=29284.460, Time=3.54 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=29299.150, Time=0.06 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=29288.301, Time=0.12 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=29288.102, Time=0.41 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=29297.992, Time=0.04 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=29284.372, Time=2.10 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=29290.093, Time=0.33 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=29290.101, Time=0.24 sec
 ARIMA(1,1,3)(0,0,0)[0] intercept   : AIC=29284.493, Time=1.98 sec
 ARIMA(0,1,3)(0,0,0)[0] intercept   : AIC=29289.281, Time=0.46 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=29283.355, Time=2.06 sec
 ARIMA(2,1,0)(0,0,0)[0] intercept   : AIC=29289.908, Time=0.19 sec
 ARIMA(3,1,1)(0,0,0)[0] intercept   : AIC=29284.421, Time=1.83 sec
 ARIMA(3,1,0)(0,0,0)[0] intercept   : AIC=29289.212, Time=0.37 sec
 ARIMA(3,1,2)(0,0,0)[0] intercept   : AIC=29284.636, Time=2.49 sec
 ARIMA(2,1,1)(0,0,0)[0]             : AIC=29282.546, Time=0.43 sec
 ARIMA(1,1,1)(0,0,0)[0]             : AIC=29288.830, Time=0.07 sec
 ARIMA(2,1,0)(0,0,0)[0]             : AIC=29288.652, Time=0.07 sec
 ARIMA(3,1,1)(0,0,0)[0]             : AIC=29283.585, Time=0.62 sec
 ARIMA(2,1,2)(0,0,0)[0]             : AIC=29283.622, Time=0.82 sec
 ARIMA(1,1,0)(0,0,0)[0]             : AIC=29287.027, Time=0.37 sec
 ARIMA(1,1,2)(0,0,0)[0]             : AIC=29283.536, Time=0.76 sec
 ARIMA(3,1,0)(0,0,0)[0]             : AIC=29288.009, Time=0.10 sec
 ARIMA(3,1,2)(0,0,0)[0]             : AIC=29283.809, Time=1.00 sec

Best model:  ARIMA(2,1,1)(0,0,0)[0]
Total fit time: 20.474 seconds
```

[112]: ARIMA(maxiter=50, method='lbfgs', order=(2, 1, 1), out_of_sample_size=0,
       scoring='mse', scoring_args={}, seasonal_order=(0, 0, 0, 0),
       start_params=None, suppress_warnings=True, trend=None,
       with_intercept=False)

[113]:
```
model_arima = ARIMA(x_train.data['Close'].values, order=(2,1,1))
```

[114]:
```
result_arima = model_arima.fit(disp=-1)
```

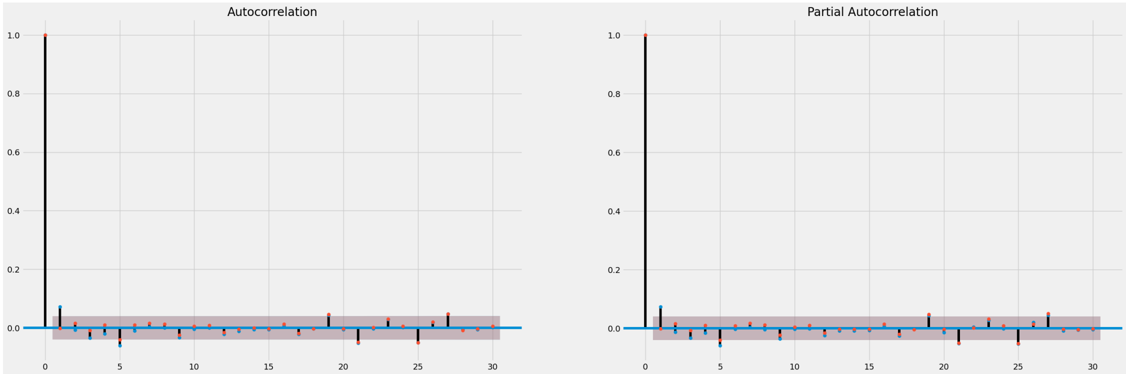
[115]:
```
print(result_arima.summary())
```

```
                             ARIMA Model Results
==============================================================================
Dep. Variable:                    D.y   No. Observations:                 2426
Model:                 ARIMA(2, 1, 1)   Log Likelihood              -14636.746
Method:                       css-mle   S.D. of innovations            100.921
Date:                Mon, 16 Nov 2020   AIC                          29283.491
Time:                        22:39:29   BIC                          29312.461
Sample:                             1   HQIC                         29294.025

==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          1.8895      1.741      1.085      0.278      -1.523       5.301
ar.L1.D.y      0.9539      0.059     16.248      0.000       0.839       1.069
ar.L2.D.y     -0.0924      0.020     -4.543      0.000      -0.132      -0.053
ma.L1.D.y     -0.8825      0.056    -15.821      0.000      -0.992      -0.773
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1            1.1840           +0.0000j            1.1840            0.0000
AR.2            9.1437           +0.0000j            9.1437            0.0000
MA.1            1.1332           +0.0000j            1.1332            0.0000
-----------------------------------------------------------------------------
```

[116]:
```
#understand residual
residuals = pd.DataFrame(result_arima.resid)
```

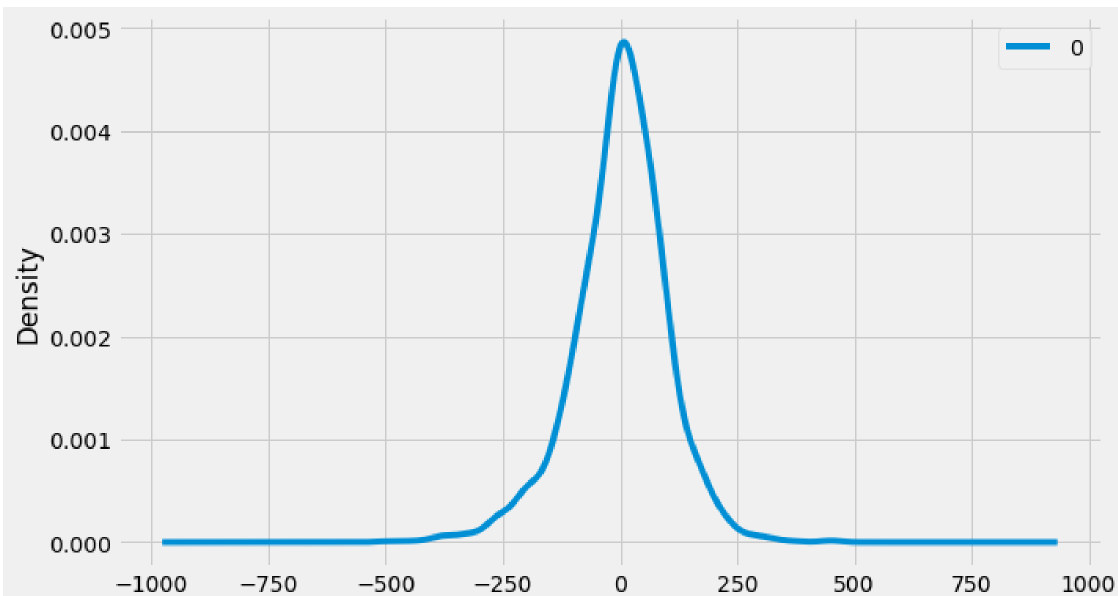
[117]:
```
plot_acf(residuals, lags=30, ax=axes[0])
plot_pacf(residuals, lags=30, ax=axes[1])
```

[117]:

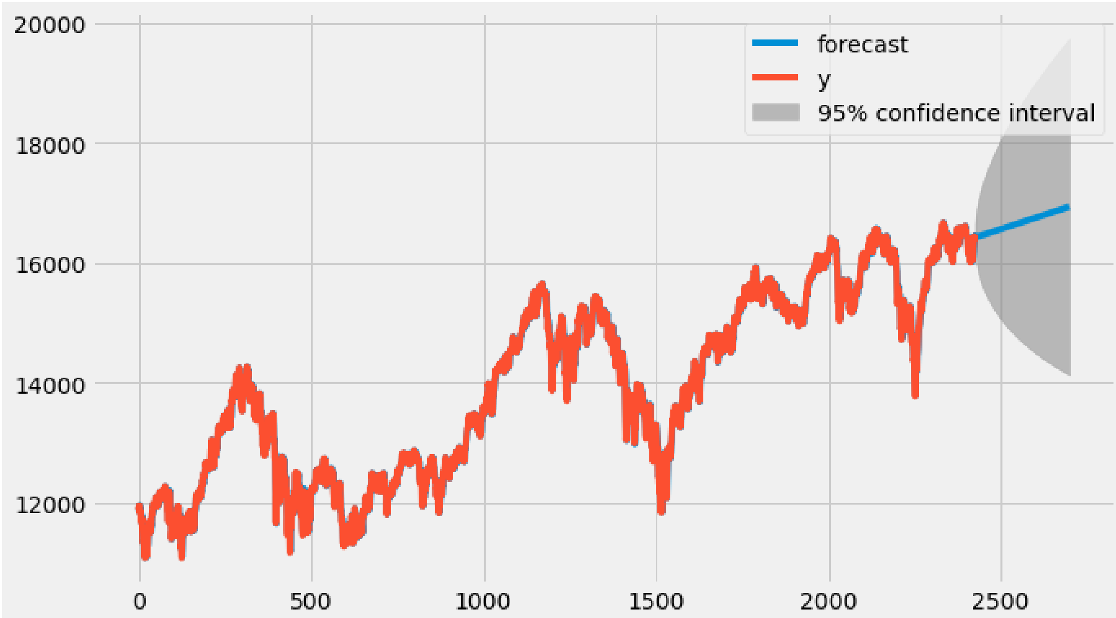


[118]:
```
residuals.plot(kind='kde')
```

[118]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9e58d08290>



[123]:
```
result_arima.plot_predict(1,2700);
```



[120]:
```
prediction = result_arima.predict(len(df)-208,len(df)-1)
def rmse(validation, prediction):
    error = validation - prediction
    return np.sqrt(np.mean(error**2))
```

[121]:
```
from statsmodels.tools.eval_measures import rmse
#RMSE for ARIMA Model
err_LSTM = rmse(x_valid.data['Close'], np.append(x_train.data.iloc[-1,:
↪]['Close'], prediction).cumsum()[1:])
print('RMSE with LSTM', err_LSTM)
```

```
RMSE with LSTM 1476.4252612252953
```

[ ]:
```

```

[ ]:
```

```

[ ]:
```
#using LSTM to predict stock price
```

[44]:
```
pip install tensorflow
```

```
Collecting tensorflow
  Using cached tensorflow-2.3.1-cp37-cp37m-manylinux2010_x86_64.whl (320.4 MB)
Requirement already satisfied: six>=1.12.0 in /opt/conda/lib/python3.7/site-
packages (from tensorflow) (1.14.0)
Collecting grpcio>=1.8.6
  Using cached grpcio-1.33.2-cp37-cp37m-manylinux2014_x86_64.whl (3.8 MB)
```

```
Collecting google-pasta>=0.1.8
  Using cached google_pasta-0.2.0-py3-none-any.whl (57 kB)
Collecting astunparse==1.6.3
  Using cached astunparse-1.6.3-py2.py3-none-any.whl (12 kB)
Requirement already satisfied: h5py<2.11.0,>=2.10.0 in
/opt/conda/lib/python3.7/site-packages (from tensorflow) (2.10.0)
Collecting keras-preprocessing<1.2,>=1.1.1
  Using cached Keras_Preprocessing-1.1.2-py2.py3-none-any.whl (42 kB)
Collecting tensorboard<3,>=2.3.0
  Using cached tensorboard-2.4.0-py3-none-any.whl (10.6 MB)
Collecting tensorflow-estimator<2.4.0,>=2.3.0
  Using cached tensorflow_estimator-2.3.0-py2.py3-none-any.whl (459 kB)
Collecting opt-einsum>=2.3.2
  Using cached opt_einsum-3.3.0-py3-none-any.whl (65 kB)
Collecting absl-py>=0.7.0
  Using cached absl_py-0.11.0-py3-none-any.whl (127 kB)
Requirement already satisfied: numpy<1.19.0,>=1.16.0 in
/opt/conda/lib/python3.7/site-packages (from tensorflow) (1.18.4)
Processing ./.cache/pip/wheels/3f/e3/ec/8a8336ff196023622fbcb36de0c5a5c218cbb241
11d1d4c7f2/termcolor-1.1.0-py3-none-any.whl
Requirement already satisfied: wheel>=0.26 in /opt/conda/lib/python3.7/site-
packages (from tensorflow) (0.34.2)
Requirement already satisfied: protobuf>=3.9.2 in /opt/conda/lib/python3.7/site-
packages (from tensorflow) (3.11.4)
Processing ./.cache/pip/wheels/62/76/4c/aa25851149f3f6d9785f6c869387ad82b3fd3758
2fa8147ac6/wrapt-1.12.1-cp37-cp37m-linux_x86_64.whl
Collecting gast==0.3.3
  Using cached gast-0.3.3-py2.py3-none-any.whl (9.7 kB)
Requirement already satisfied: requests<3,>=2.21.0 in
/opt/conda/lib/python3.7/site-packages (from tensorboard<3,>=2.3.0->tensorflow)
(2.23.0)
Requirement already satisfied: setuptools>=41.0.0 in
/opt/conda/lib/python3.7/site-packages (from tensorboard<3,>=2.3.0->tensorflow)
(46.1.3.post20200325)
Collecting werkzeug>=0.11.15
  Using cached Werkzeug-1.0.1-py2.py3-none-any.whl (298 kB)
Collecting markdown>=2.6.8
  Using cached Markdown-3.3.3-py3-none-any.whl (96 kB)
Collecting tensorboard-plugin-wit>=1.6.0
  Using cached tensorboard_plugin_wit-1.7.0-py3-none-any.whl (779 kB)
Collecting google-auth-oauthlib<0.5,>=0.4.1
  Using cached google_auth_oauthlib-0.4.2-py2.py3-none-any.whl (18 kB)
Requirement already satisfied: google-auth<2,>=1.6.3 in
/opt/conda/lib/python3.7/site-packages (from tensorboard<3,>=2.3.0->tensorflow)
(1.16.1)
Requirement already satisfied: idna<3,>=2.5 in /opt/conda/lib/python3.7/site-
packages (from requests<3,>=2.21.0->tensorboard<3,>=2.3.0->tensorflow) (2.9)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in
```

```
/opt/conda/lib/python3.7/site-packages (from
requests<3,>=2.21.0->tensorboard<3,>=2.3.0->tensorflow) (1.25.9)
Requirement already satisfied: certifi>=2017.4.17 in
/opt/conda/lib/python3.7/site-packages (from
requests<3,>=2.21.0->tensorboard<3,>=2.3.0->tensorflow) (2020.4.5.2)
Requirement already satisfied: chardet<4,>=3.0.2 in
/opt/conda/lib/python3.7/site-packages (from
requests<3,>=2.21.0->tensorboard<3,>=2.3.0->tensorflow) (3.0.4)
Requirement already satisfied: importlib-metadata; python_version < "3.8" in
/opt/conda/lib/python3.7/site-packages (from
markdown>=2.6.8->tensorboard<3,>=2.3.0->tensorflow) (1.6.0)
Requirement already satisfied: requests-oauthlib>=0.7.0 in
/opt/conda/lib/python3.7/site-packages (from google-auth-
oauthlib<0.5,>=0.4.1->tensorboard<3,>=2.3.0->tensorflow) (1.3.0)
Requirement already satisfied: pyasn1-modules>=0.2.1 in
/opt/conda/lib/python3.7/site-packages (from google-
auth<2,>=1.6.3->tensorboard<3,>=2.3.0->tensorflow) (0.2.8)
Requirement already satisfied: rsa<4.1,>=3.1.4 in /opt/conda/lib/python3.7/site-
packages (from google-auth<2,>=1.6.3->tensorboard<3,>=2.3.0->tensorflow) (4.0)
Requirement already satisfied: cachetools<5.0,>=2.0.0 in
/opt/conda/lib/python3.7/site-packages (from google-
auth<2,>=1.6.3->tensorboard<3,>=2.3.0->tensorflow) (4.1.0)
Requirement already satisfied: zipp>=0.5 in /opt/conda/lib/python3.7/site-
packages (from importlib-metadata; python_version <
"3.8"->markdown>=2.6.8->tensorboard<3,>=2.3.0->tensorflow) (3.1.0)
Requirement already satisfied: oauthlib>=3.0.0 in /opt/conda/lib/python3.7/site-
packages (from requests-oauthlib>=0.7.0->google-auth-
oauthlib<0.5,>=0.4.1->tensorboard<3,>=2.3.0->tensorflow) (3.0.1)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in
/opt/conda/lib/python3.7/site-packages (from pyasn1-modules>=0.2.1->google-
auth<2,>=1.6.3->tensorboard<3,>=2.3.0->tensorflow) (0.4.8)
Installing collected packages: grpcio, google-pasta, astunparse, keras-
preprocessing, absl-py, werkzeug, markdown, tensorboard-plugin-wit, google-auth-
oauthlib, tensorboard, tensorflow-estimator, opt-einsum, termcolor, wrapt, gast,
tensorflow
Successfully installed absl-py-0.11.0 astunparse-1.6.3 gast-0.3.3 google-auth-
oauthlib-0.4.2 google-pasta-0.2.0 grpcio-1.33.2 keras-preprocessing-1.1.2
markdown-3.3.3 opt-einsum-3.3.0 tensorboard-2.4.0 tensorboard-plugin-wit-1.7.0
tensorflow-2.3.1 tensorflow-estimator-2.3.0 termcolor-1.1.0 werkzeug-1.0.1
wrapt-1.12.1
Note: you may need to restart the kernel to use updated packages.
```

[45]:
```
pip install keras
```

```
Collecting keras
  Using cached Keras-2.4.3-py2.py3-none-any.whl (36 kB)
Requirement already satisfied: scipy>=0.14 in /opt/conda/lib/python3.7/site-
packages (from keras) (1.4.1)
```

```
Requirement already satisfied: numpy>=1.9.1 in /opt/conda/lib/python3.7/site-
packages (from keras) (1.18.4)
Requirement already satisfied: h5py in /opt/conda/lib/python3.7/site-packages
(from keras) (2.10.0)
Requirement already satisfied: pyyaml in /opt/conda/lib/python3.7/site-packages
(from keras) (5.3.1)
Requirement already satisfied: six in /opt/conda/lib/python3.7/site-packages
(from h5py->keras) (1.14.0)
Installing collected packages: keras
Successfully installed keras-2.4.3
Note: you may need to restart the kernel to use updated packages.
```

[46]:
```
pip install pandas-datareader
```

```
Requirement already satisfied: pandas-datareader in
/opt/conda/lib/python3.7/site-packages (0.9.0)
Requirement already satisfied: lxml in /opt/conda/lib/python3.7/site-packages
(from pandas-datareader) (4.5.1)
Requirement already satisfied: requests>=2.19.0 in
/opt/conda/lib/python3.7/site-packages (from pandas-datareader) (2.23.0)
Requirement already satisfied: pandas>=0.23 in /opt/conda/lib/python3.7/site-
packages (from pandas-datareader) (1.0.3)
Requirement already satisfied: certifi>=2017.4.17 in
/opt/conda/lib/python3.7/site-packages (from requests>=2.19.0->pandas-
datareader) (2020.4.5.2)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in
/opt/conda/lib/python3.7/site-packages (from requests>=2.19.0->pandas-
datareader) (1.25.9)
Requirement already satisfied: chardet<4,>=3.0.2 in
/opt/conda/lib/python3.7/site-packages (from requests>=2.19.0->pandas-
datareader) (3.0.4)
Requirement already satisfied: idna<3,>=2.5 in /opt/conda/lib/python3.7/site-
packages (from requests>=2.19.0->pandas-datareader) (2.9)
Requirement already satisfied: python-dateutil>=2.6.1 in
/opt/conda/lib/python3.7/site-packages (from pandas>=0.23->pandas-datareader)
(2.8.1)
Requirement already satisfied: pytz>=2017.2 in /opt/conda/lib/python3.7/site-
packages (from pandas>=0.23->pandas-datareader) (2020.1)
Requirement already satisfied: numpy>=1.13.3 in /opt/conda/lib/python3.7/site-
packages (from pandas>=0.23->pandas-datareader) (1.18.4)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.7/site-
packages (from python-dateutil>=2.6.1->pandas>=0.23->pandas-datareader) (1.14.0)
Note: you may need to restart the kernel to use updated packages.
```

[47]:
```
from pandas_datareader import data
import datetime as dt
from matplotlib import pyplot as plt
```

```
from sklearn import model_selection
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Dropout
```

[48]:
```
#similar to before, upload NASDAQ data
df=pd.read_csv("IXIC_v1.csv", sep=",")
from datetime import datetime
con=df['Date']
df['Date']=pd.to_datetime(df['Date'])
df.set_index('Date', inplace=True)
test = df[2164:]
train = df[:2163]
```

[49]:
```
df['Date'] = df.index
data2 = pd.DataFrame(columns = ['Date', 'Close'])
data2['Date'] = df['Date']
data2['Close'] = df['Close']
```

[50]:
```
#scale and reshape data
train_set = data2.iloc[:, 1:2].values
sc = MinMaxScaler(feature_range = (0, 1))
training_set_scaled = sc.fit_transform(train_set)
X_train = []
y_train = []
for i in range(60, 2600):
    X_train.append(training_set_scaled[i-60:i, 0])
    y_train.append(training_set_scaled[i, 0])
X_train, y_train = np.array(X_train), np.array(y_train)
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
```

[51]:
```
#add layers
regressor = Sequential()
regressor.add(LSTM(units = 50, return_sequences = True, input_shape = (X_train.
 ↪shape[1], 1)))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))
```

```
regressor.add(LSTM(units = 50))
regressor.add(Dropout(0.2))
regressor.add(Dense(units = 1))
```

[52]:
```
#add optimizer and build model
regressor.compile(optimizer = 'adam', loss = 'mean_squared_error')
regressor.fit(X_train, y_train, epochs = 35, batch_size = 30)
```

```
Epoch 1/35
85/85 [==============================] - 13s 148ms/step - loss: 0.0072
Epoch 2/35
85/85 [==============================] - 12s 144ms/step - loss: 0.0021
Epoch 3/35
85/85 [==============================] - 12s 144ms/step - loss: 0.0016
Epoch 4/35
85/85 [==============================] - 12s 143ms/step - loss: 0.0014
Epoch 5/35
85/85 [==============================] - 12s 141ms/step - loss: 0.0014
Epoch 6/35
85/85 [==============================] - 12s 138ms/step - loss: 0.0014
Epoch 7/35
85/85 [==============================] - 12s 139ms/step - loss: 0.0012
Epoch 8/35
85/85 [==============================] - 12s 138ms/step - loss: 0.0012
Epoch 9/35
85/85 [==============================] - 12s 141ms/step - loss: 0.0012
Epoch 10/35
85/85 [==============================] - 12s 139ms/step - loss: 0.0010
Epoch 11/35
85/85 [==============================] - 13s 151ms/step - loss: 0.0011
Epoch 12/35
85/85 [==============================] - 12s 136ms/step - loss: 0.0013
Epoch 13/35
85/85 [==============================] - 12s 138ms/step - loss: 9.7515e-04
Epoch 14/35
85/85 [==============================] - 12s 139ms/step - loss: 9.1828e-04
Epoch 15/35
85/85 [==============================] - 12s 138ms/step - loss: 9.6688e-04
Epoch 16/35
85/85 [==============================] - 12s 138ms/step - loss: 8.8376e-04
Epoch 17/35
85/85 [==============================] - 12s 137ms/step - loss: 0.0010
Epoch 18/35
85/85 [==============================] - 12s 137ms/step - loss: 8.9150e-04
Epoch 19/35
85/85 [==============================] - 12s 139ms/step - loss: 7.4694e-04
Epoch 20/35
```

```
85/85 [==============================] - 12s 139ms/step - loss: 7.7914e-04
Epoch 21/35
85/85 [==============================] - 12s 139ms/step - loss: 6.5991e-04
Epoch 22/35
85/85 [==============================] - 14s 159ms/step - loss: 7.2176e-04
Epoch 23/35
85/85 [==============================] - 12s 138ms/step - loss: 6.7855e-04
Epoch 24/35
85/85 [==============================] - 13s 152ms/step - loss: 6.6344e-04
Epoch 25/35
85/85 [==============================] - 12s 137ms/step - loss: 6.5142e-04
Epoch 26/35
85/85 [==============================] - 12s 137ms/step - loss: 7.8931e-04
Epoch 27/35
85/85 [==============================] - 12s 136ms/step - loss: 5.9459e-04
Epoch 28/35
85/85 [==============================] - 12s 136ms/step - loss: 6.9213e-04
Epoch 29/35
85/85 [==============================] - 12s 136ms/step - loss: 6.2773e-04
Epoch 30/35
85/85 [==============================] - 12s 136ms/step - loss: 5.7058e-04
Epoch 31/35
85/85 [==============================] - 11s 134ms/step - loss: 6.6173e-04
Epoch 32/35
85/85 [==============================] - 11s 133ms/step - loss: 6.5656e-04
Epoch 33/35
85/85 [==============================] - 11s 134ms/step - loss: 6.3707e-04
Epoch 34/35
85/85 [==============================] - 12s 136ms/step - loss: 6.2015e-04
Epoch 35/35
85/85 [==============================] - 11s 135ms/step - loss: 5.4213e-04
```

[52]:

```
<tensorflow.python.keras.callbacks.History at 0x7f9ed0142a10>
```

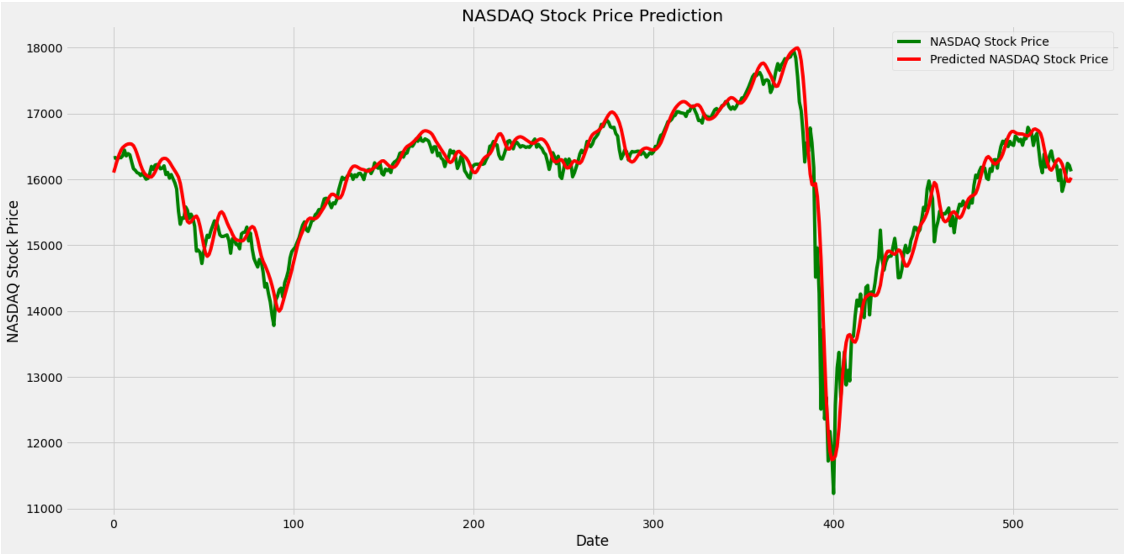
[70]:

```python
#train the model
testdataframe= test
testdataframe['Date'] = testdataframe.index
testdata = pd.DataFrame(columns = ['Date','Close'])
testdata['Date'] = testdataframe['Date']
testdata['Close'] = testdataframe['Close']
real_stock_price = testdata.iloc[:, 1:2].values
dataset_total = pd.concat((data2['Close'], testdata['Close']), axis = 0)
inputs = dataset_total[len(dataset_total) - len(testdata) - 60:].values
inputs = inputs.reshape(-1,1)
inputs = sc.transform(inputs)
X_test = []
for i in range(60, 601):
```

```
    X_test.append(inputs[i-60:i, 0])
X_test = np.array(X_test)
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
```

[71]:
```
predicted_stock_price = regressor.predict(X_test)
predicted_stock_price = sc.inverse_transform(predicted_stock_price)
```

[151]:
```
plt.figure(figsize=(20,10))
plt.plot(real_stock_price, color = 'green', label = 'NASDAQ Stock Price')
plt.plot(predicted_stock_price, color = 'red', label = 'Predicted NASDAQ Stock␣
 ↪Price')
plt.title('NASDAQ Stock Price Prediction')
plt.xlabel('Date')
plt.ylabel('NASDAQ Stock Price')
plt.legend()
plt.show()
```



[74]:
```
rmse_predict= np.reshape(predicted_stock_price,541)
```

[75]:
```
test["Close"].values.shape
```

[75]: (541,)

[76]:
```
rmse_predict.shape
```

[76]: (541,)

[77]:
```
#RMSE for LSTM Model
err_LSTM = rmse(test["Close"].values, rmse_predict)
print('RMSE with LSTM', err_LSTM)
```

```
RMSE with LSTM 396.96105468494505
```

[124]:
```
#repeat the same process for TSX
df=pd.read_csv("GSPTSE_v1.csv", sep=",")
from datetime import datetime
con=df['Date']
df['Date']=pd.to_datetime(df['Date'])
df.set_index('Date', inplace=True)
test = df[2164:]
train = df[:2163]
```

[125]:
```
df['Date'] = df.index
data2 = pd.DataFrame(columns = ['Date', 'Close'])
data2['Date'] = df['Date']
data2['Close'] = df['Close']
```

[134]:
```
train_set = data2.iloc[:, 1:2].values
sc = MinMaxScaler(feature_range = (0, 1))
training_set_scaled = sc.fit_transform(train_set)
X_train = []
y_train = []
for i in range(60, 2600):
    X_train.append(training_set_scaled[i-60:i, 0])
    y_train.append(training_set_scaled[i, 0])
X_train, y_train = np.array(X_train), np.array(y_train)
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
```

[135]:
```
regressor = Sequential()
regressor.add(LSTM(units = 50, return_sequences = True, input_shape = (X_train.
 ↪shape[1], 1)))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units = 50))
regressor.add(Dropout(0.2))
regressor.add(Dense(units = 1))
```

[136]:
```
regressor.compile(optimizer = 'adam', loss = 'mean_squared_error')
regressor.fit(X_train, y_train, epochs = 30, batch_size = 32)
```

```
Epoch 1/30
```

```
80/80 [==============================] - 13s 164ms/step - loss: 0.0242
Epoch 2/30
80/80 [==============================] - 11s 140ms/step - loss: 0.0065
Epoch 3/30
80/80 [==============================] - 11s 136ms/step - loss: 0.0059
Epoch 4/30
80/80 [==============================] - 11s 135ms/step - loss: 0.0060
Epoch 5/30
80/80 [==============================] - 11s 134ms/step - loss: 0.0050
Epoch 6/30
80/80 [==============================] - 11s 134ms/step - loss: 0.0046
Epoch 7/30
80/80 [==============================] - 11s 133ms/step - loss: 0.0039
Epoch 8/30
80/80 [==============================] - 11s 132ms/step - loss: 0.0040
Epoch 9/30
80/80 [==============================] - 10s 130ms/step - loss: 0.0037
Epoch 10/30
80/80 [==============================] - 10s 129ms/step - loss: 0.0033
Epoch 11/30
80/80 [==============================] - 10s 130ms/step - loss: 0.0032
Epoch 12/30
80/80 [==============================] - 10s 126ms/step - loss: 0.0030
Epoch 13/30
80/80 [==============================] - 10s 125ms/step - loss: 0.0033
Epoch 14/30
80/80 [==============================] - 10s 125ms/step - loss: 0.0028
Epoch 15/30
80/80 [==============================] - 10s 124ms/step - loss: 0.0029
Epoch 16/30
80/80 [==============================] - 10s 125ms/step - loss: 0.0026
Epoch 17/30
80/80 [==============================] - 10s 126ms/step - loss: 0.0029
Epoch 18/30
80/80 [==============================] - 10s 126ms/step - loss: 0.0025
Epoch 19/30
80/80 [==============================] - 10s 126ms/step - loss: 0.0026
Epoch 20/30
80/80 [==============================] - 10s 126ms/step - loss: 0.0026
Epoch 21/30
80/80 [==============================] - 10s 126ms/step - loss: 0.0024
Epoch 22/30
80/80 [==============================] - 12s 151ms/step - loss: 0.0023
Epoch 23/30
80/80 [==============================] - 10s 127ms/step - loss: 0.0024
Epoch 24/30
80/80 [==============================] - 10s 124ms/step - loss: 0.0022
Epoch 25/30
```

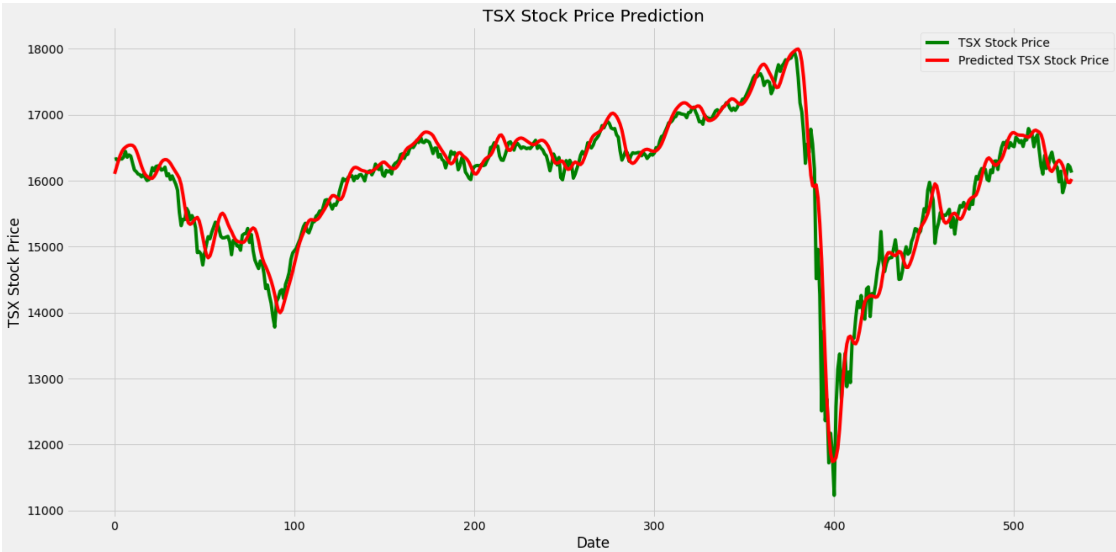
```
80/80 [==============================] - 10s 124ms/step - loss: 0.0021
Epoch 26/30
80/80 [==============================] - 10s 123ms/step - loss: 0.0020
Epoch 27/30
80/80 [==============================] - 10s 123ms/step - loss: 0.0018
Epoch 28/30
80/80 [==============================] - 10s 126ms/step - loss: 0.0021
Epoch 29/30
80/80 [==============================] - 10s 130ms/step - loss: 0.0020
Epoch 30/30
80/80 [==============================] - 11s 133ms/step - loss: 0.0020
```

[136]:
```
<tensorflow.python.keras.callbacks.History at 0x7f9e36958150>
```

[143]:
```
testdataframe= test
testdataframe['Date'] = testdataframe.index
testdata = pd.DataFrame(columns = ['Date','Close'])
testdata['Date'] = testdataframe['Date']
testdata['Close'] = testdataframe['Close']
real_stock_price = testdata.iloc[:, 1:2].values
dataset_total = pd.concat((data2['Close'], testdata['Close']), axis = 0)
inputs = dataset_total[len(dataset_total) - len(testdata) - 60:].values
inputs = inputs.reshape(-1,1)
inputs = sc.transform(inputs)
X_test = []
for i in range(60, 593):
    X_test.append(inputs[i-60:i, 0])
X_test = np.array(X_test)
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
```

[144]:
```
predicted_stock_price = regressor.predict(X_test)
predicted_stock_price = sc.inverse_transform(predicted_stock_price)
```

[152]:
```
plt.figure(figsize=(20,10))
plt.plot(real_stock_price, color = 'green', label = 'TSX Stock Price')
plt.plot(predicted_stock_price, color = 'red', label = 'Predicted TSX Stock␣
 ↪Price')
plt.title('TSX Stock Price Prediction')
plt.xlabel('Date')
plt.ylabel('TSX Stock Price')
plt.legend()
plt.show()
```



[147]:
```
rmse_predict= np.reshape(predicted_stock_price,533)
```

[148]:
```
test["Close"].values.shape
```

[148]: (533,)

[149]:
```
rmse_predict.shape
```

[149]: (533,)

[150]:
```
#RMSE for LSTM Model
err_LSTM = rmse(test["Close"].values, rmse_predict)
print('RMSE with LSTM', err_LSTM)
```

RMSE with LSTM 265.51210144690225

[ ]: