Project Overview

- Covid 19 has med the Stock market very volatime in the last few months.
- You have been assigned to attempt to forecast the value of the S&P one day forward into the future

Poject Approach

- Create a model that will train on data from the begining of 2020 until current data
- This will capture the behavior during Covid 19
- Back test this model 2 months back to test accuracy
- Create predictions for a certain period to test the precision of the model before forecasting

Data Fetching

- Will download data from Yahoo Finance API via Pandas

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:
```
from pandas_datareader import data as web
```

```
/home/ubuntu/anaconda3/lib/python3.7/site-packages/pandas_datareader/co
mpat/__init__.py:7: FutureWarning: pandas.util.testing is deprecated. U
se the functions in the public API at pandas.testing instead.
  from pandas.util.testing import assert_frame_equal
```

In [3]:
```
data = pd.DataFrame(web.DataReader("^GSPC", data_source = "yahoo", start
= "2020-1-1")["Adj Close"])
```

In [4]:
```
data.info()
```

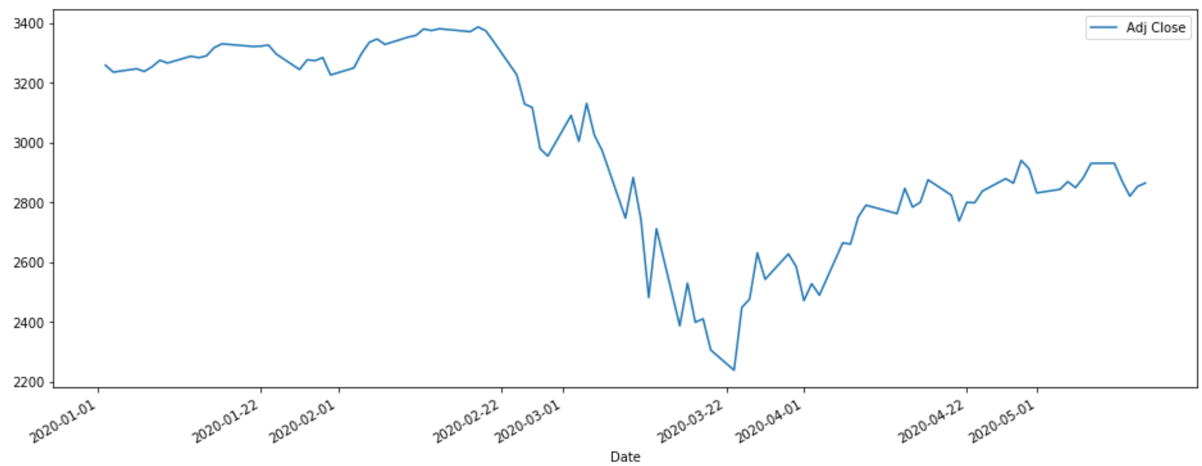
```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 94 entries, 2020-01-02 to 2020-05-15
Data columns (total 1 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Adj Close  94 non-null     float64
dtypes: float64(1)
memory usage: 1.5 KB
```

initial Analysis

- The effects of COVID on the market can be seen mostly at the Beginning of March
- The market took a steady climb back from Early april to current where we see some sign of "normal"bahavior
- Volatility in the market shows more of an increase since April 1 2020

In [5]:
```
data.plot(figsize = (16,6))
```

Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x7fda7daff610>



Preparing our data

- What the approach should be here is to take a good amount of data out of this set to train on and validate again a teting set.
- Because of the high volatility in the data we should expect a lower accuracy in predictions. A good way of overriding this issue is maybe to gather a larger time frame of data
- Becaue we have approximately 3+ months (trading days) of data we will test on 30 days and train on 2 months approximately. THis is not a larget sum of data but could give us some insight on the movement of the market

In [6]:
```
testing_sample = 30
```

In [7]:
```
testing_index = len(data) - testing_sample
```

In [8]:
```
train = data.iloc[:testing_index]
```

In [9]:
```
test = data.iloc[testing_index:]
```

In [10]:
```
train.shape
```

Out[10]: (64, 1)

In [11]:
```
test.shape
```
Out[11]:
```
(30, 1)
```

Scaling the data

- Will scale to consider the full range in the standard deviation of the data
- Model will be abel to consider all outliers in training

In [12]:
```
from sklearn.preprocessing import MinMaxScaler
```
In [13]:
```
scalar = MinMaxScaler()
```
In [14]:
```
train_scaled = scalar.fit_transform(train)
```
In [15]:
```
test_scaled = scalar.transform(test)
```
In [16]:
```
train_scaled.shape
```
Out[16]:
```
(64, 1)
```
In [17]:
```
test_scaled.shape
```
Out[17]:
```
(30, 1)
```

Time Series Generator

- Will use a generator to train our data using a specified length of time to attempt to predict
- Since we are only aiming to predict one feature we will use a feature count of 1
- Length to attempt to predict will be 5 trading days though we are aiming for 1 day our
- The first prediciton on the LSTM model is more accurate do to gradient decay

In [18]:
```
length =5
n_features = 1
```
In [19]:
```
from tensorflow.keras.preprocessing.sequence import TimeseriesGenerator
```
In [20]:
```
gen = TimeseriesGenerator(train_scaled,train_scaled, length = length, ba
tch_size=1)
```

Validation Data

- Will use to put our training data up again to improve training

In [21]:
```
vali_gen = TimeseriesGenerator(test_scaled,test_scaled, length=length, b
atch_size=1)
```

Early Stopping

- Will use to prevent Over Training of the model

In [22]:
```
from tensorflow.keras.callbacks import TensorBoard,EarlyStopping
```

In [23]:
```
stop = EarlyStopping(monitor="val_loss", mode = "max", patience= 60)
```

Model Creation

- We will use a LSTM model for improvement in predictions. LSTM is a better training model since it will take into account Gradient Decay

In [24]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM
```

In [25]:
```
model = Sequential()
model.add(LSTM(units=400, activation = "relu", input_shape = (length,n_f
eatures)))
model.add(Dense(units = 1))
model.compile(loss = "mse", optimizer = "adam")
```

Fittiing Model

- Will fit model to the generator , validation data, a high epoch, and use early stopping to precvent over training

In [26]:
```
model.fit_generator(generator=gen, validation_data=vali_gen, epochs=100,
callbacks=[stop])
```

```
Epoch 1/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0801 -
val_loss: 0.0023
Epoch 2/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0141 -
val_loss: 0.0038
Epoch 3/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0154 -
val_loss: 0.0097
Epoch 4/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0248 -
val_loss: 0.0198
Epoch 5/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0177 -
val_loss: 0.0060
Epoch 6/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0128 -
val_loss: 0.0096
Epoch 7/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0145 -
val_loss: 0.0055
Epoch 8/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0142 -
val_loss: 0.0072
Epoch 9/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0129 -
val_loss: 0.0031
Epoch 10/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0176 -
val_loss: 0.0095
Epoch 11/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0113 -
val_loss: 0.0074
Epoch 12/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0107 -
val_loss: 0.0230
Epoch 13/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0109 -
val_loss: 0.0103
Epoch 14/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0106 -
val_loss: 0.0059
Epoch 15/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0090 -
val_loss: 0.0139
Epoch 16/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0084 -
val_loss: 0.0120
Epoch 17/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0089 -
val_loss: 0.0081
Epoch 18/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0092 -
val_loss: 0.0186
Epoch 19/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0074 -
val_loss: 0.0120
```

```
Epoch 20/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0072 -
val_loss: 0.0175
Epoch 21/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0095 -
val_loss: 0.0029
Epoch 22/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0113 -
val_loss: 0.0067
Epoch 23/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0075 -
val_loss: 0.0202
Epoch 24/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0084 -
val_loss: 0.0160
Epoch 25/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0078 -
val_loss: 0.0166
Epoch 26/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0073 -
val_loss: 0.0094
Epoch 27/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0066 -
val_loss: 0.0079
Epoch 28/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0082 -
val_loss: 0.0062
Epoch 29/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0071 -
val_loss: 0.0074
Epoch 30/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0069 -
val_loss: 0.0051
Epoch 31/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0059 -
val_loss: 0.0083
Epoch 32/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0062 -
val_loss: 0.0092
Epoch 33/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0061 -
val_loss: 0.0068
Epoch 34/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0077 -
val_loss: 0.0034
Epoch 35/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0062 -
val_loss: 0.0129
Epoch 36/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0060 -
val_loss: 0.0116
Epoch 37/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0081 -
val_loss: 0.0140
Epoch 38/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0090 -
val_loss: 0.0129
```

```
Epoch 39/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0067 -
val_loss: 0.0061
Epoch 40/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0055 -
val_loss: 0.0059
Epoch 41/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0058 -
val_loss: 0.0062
Epoch 42/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0055 -
val_loss: 0.0046
Epoch 43/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0052 -
val_loss: 0.0063
Epoch 44/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0058 -
val_loss: 0.0066
Epoch 45/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0061 -
val_loss: 0.0041
Epoch 46/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0080 -
val_loss: 0.0024
Epoch 47/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0062 -
val_loss: 0.0054
Epoch 48/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0068 -
val_loss: 0.0042
Epoch 49/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0053 -
val_loss: 0.0068
Epoch 50/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0057 -
val_loss: 0.0032
Epoch 51/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0073 -
val_loss: 0.0039
Epoch 52/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0070 -
val_loss: 0.0050
Epoch 53/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0044 -
val_loss: 0.0193
Epoch 54/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0064 -
val_loss: 0.0037
Epoch 55/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0054 -
val_loss: 0.0080
Epoch 56/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0051 -
val_loss: 0.0043
Epoch 57/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0053 -
val_loss: 0.0047
```

```
Epoch 58/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0060 -
val_loss: 0.0044
Epoch 59/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0049 -
val_loss: 0.0078
Epoch 60/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0051 -
val_loss: 0.0035
Epoch 61/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0055 -
val_loss: 0.0057
Epoch 62/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0048 -
val_loss: 0.0036
Epoch 63/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0050 -
val_loss: 0.0047
Epoch 64/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0048 -
val_loss: 0.0042
Epoch 65/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0046 -
val_loss: 0.0061
Epoch 66/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0047 -
val_loss: 0.0046
Epoch 67/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0043 -
val_loss: 0.0062
Epoch 68/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0048 -
val_loss: 0.0125
Epoch 69/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0080 -
val_loss: 0.0056
Epoch 70/100
59/59 [==============================] - 2s 30ms/step - loss: 0.0061 -
val_loss: 0.0024
Epoch 71/100
59/59 [==============================] - 2s 29ms/step - loss: 0.0065 -
val_loss: 0.0025
Epoch 72/100
59/59 [==============================] - 2s 31ms/step - loss: 0.0050 -
val_loss: 0.0032
```

Out[26]:

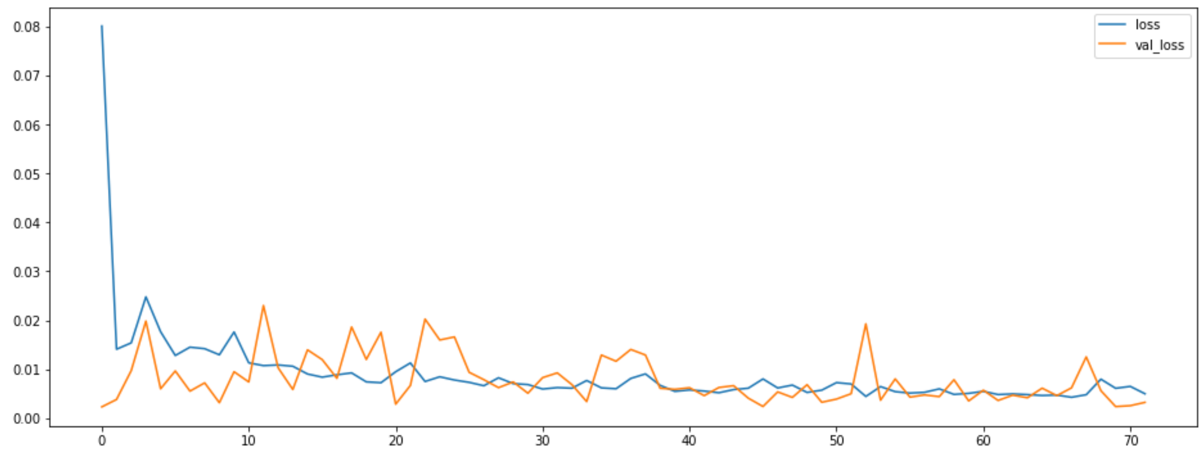
```
<tensorflow.python.keras.callbacks.History at 0x7fda68084fd0>
```

Model Performance

- Lets see the results of the model training
- looks like our model performed very well
- We will take a look at theprodictions below
- We will save this model for future Predictions

In [27]:
```
pd.DataFrame(model.history.history).plot(figsize = (16,6))
```

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x7fda506f2bd0>



In [59]:
```
# model.save("sandpModel.h5")
```

In [60]:
```
model_his = pd.DataFrame(model.history.history)
```

In [61]:
```
#model_his.to_csv("model_history.csv")
```

Model Predictions

- We will predict the test values range from our test data set
- This will tell us how accurate our model is on a first day prediciton before forecasting

In [29]:
```
test_predicitons = []
batch = train_scaled[-length:]
current_batch = batch.reshape((1,length,n_features))
for i in range(len(test)):
    prediction = model.predict(current_batch)[0]
    test_predicitons.append(prediction)
    current_batch = np.append(current_batch[:,1:,:], [[prediction]], axi
s =1)
```

inverse Scaling

- The data was trained on scaled data so to get the true values of the predicitons we need to inverse the scaling
- we will match the predictions data with our test data to check performance

In [30]:
```
true_predictions = scalar.inverse_transform(test_predicitons)
```

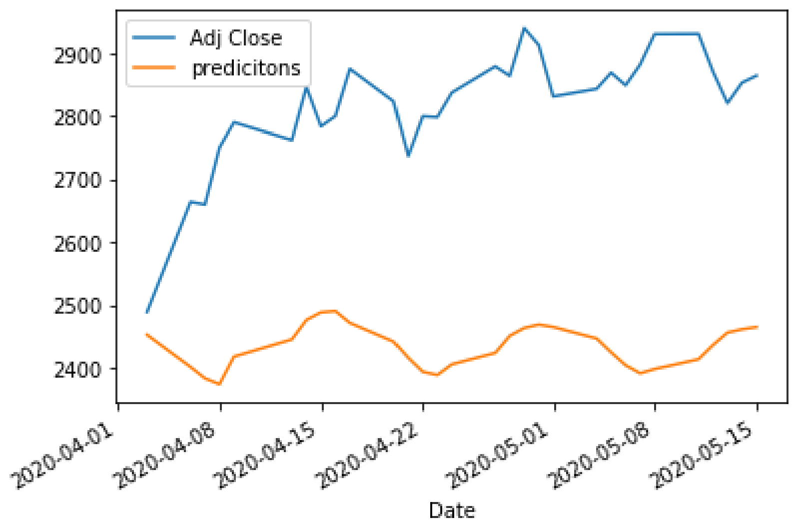
In [31]:
```
test["predicitons"] = true_predictions
```

```
/home/ubuntu/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.p
y:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

In [32]:
```
test.plot()
```

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x7fda3026fed0>



Model Accuracy

- Model predicted the Value of S&P to bte 2496.5 adn the true value on 2020-4-3 was 2488.6.. This was pretty accurate,
- We can now try to forecast on this model

In [33]:
```
test.head(1)
```

Out[33]:

	Adj Close	predicitons
Date		
2020-04-03	2488.649902	2452.210939

Forecasting

- We will forecast 5 daty ahead of out data set using the data we cllected for the covid time frame
- We Must first scale our data before forecasting

In [34]:
```
data_scalar = MinMaxScaler()
```

In [35]:
```
data_scaled = data_scalar.fit_transform(data)
```

In [36]:
```
data_scaled.shape
```

Out[36]:
```
(94, 1)
```

In [37]:
```
forecast = []
periods = length
bb = data_scaled[-length:]
curr_b = bb.reshape(1,length,n_features)
for l in range(periods):
    predict = model.predict(curr_b)[0]
    forecast.append(predict)
    curr_b = np.append(curr_b[:,1:,:], [[predict]], axis = 1)
```

Inverse forecast

- We will need to inverse the scaled data to get the true forecast

In [38]:
```
true_Forecast = data_scalar.inverse_transform(forecast)
```

In [39]:
```
true_Forecast
```

Out[39]:
```
array([[2816.80655017],
       [2815.74997671],
       [2787.42591999],
       [2764.0325851 ],
       [2740.13701662]])
```

Time Series

- We need a time series for our 5 day forecast
- We will begin one day ahead of the end of our data series seen below

In [40]:
```
data.tail().iloc[-1:].reset_index().iloc[0]["Date"]
```

Out[40]:
```
Timestamp('2020-05-15 00:00:00')
```

In [41]:
```
forecast_period = pd.date_range(start = "2020-05-16", periods=periods, f
req="B")
```

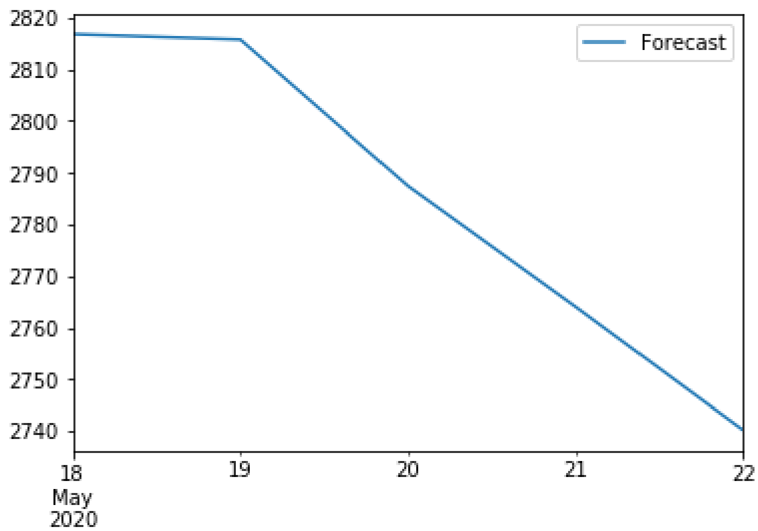
In [42]:
```
forecast_df = pd.DataFrame(true_Forecast,index=forecast_period, columns=
["Forecast"])
```

Forecast Consideration

- We will only consider the forecast for the first day forward in our case 2020-5-18

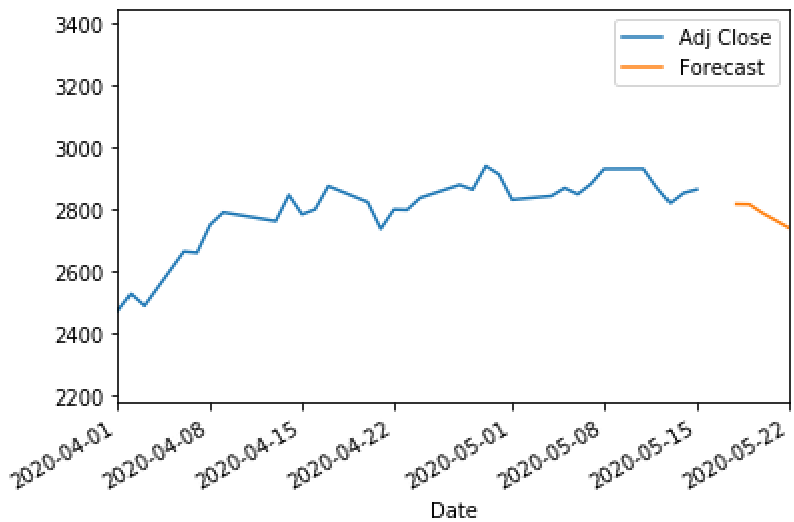
In [43]:
```
forecast_df.plot()
```

Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x7fda1077bb10>



plot with data

In [44]:
```
ax = data.plot()
forecast_df.plot(ax = ax)
plt.xlim("2020-4-1", "2020-5-22");
```



In [45]:
```
forecast_df.head(1)
```

Out[45]:

	Forecast
2020-05-18	2816.80655

In [46]:
```
data.tail().iloc[-1:]
```

Out[46]:

	Adj Close
Date	
2020-05-15	2863.699951

Summary Of model Predictions

- Model predicts the ADJ close for the market for 5-18-2020 will be 2794.72
- Where are the previsous day was 2863.69

Back Test

- Lets take out model back a bit to see how it will forecast
- This will give us a sense of if our forecast above has a chance of being accurate
- We will take a few weeks/days off the data set

Forecasting on backtest

- We will aim to forecast on the the day after 2020-5-4 with our model

In [47]:
```
back_test = data.loc["2020-1-2":"2020-5-4"]
```

In [48]:
```
back_test
```

Out[48]:

	Adj Close
Date	
2020-01-02	3257.850098
2020-01-03	3234.850098
2020-01-06	3246.280029
2020-01-07	3237.179932
2020-01-08	3253.050049
...	...
2020-04-28	2863.389893
2020-04-29	2939.510010
2020-04-30	2912.429932
2020-05-01	2830.709961
2020-05-04	2842.739990

85 rows × 1 columns

In [49]:
```
back_test_Scalar = MinMaxScaler()
```

In [50]:
```
back_test_scaled = back_test_Scalar.fit_transform(back_test)
```

In [51]:
```
backtest_forecast = []
perio = length
b = back_test_scaled[-length:]
bb_curr = b.reshape(1,length,n_features)
for i in range(perio):
    pre = model.predict(bb_curr)[0]
    backtest_forecast.append(pre)
    bb_curr = np.append(bb_curr[:,1:,:], [[pre]], axis=1)
```

In [52]:
```
true_back_forecast = back_test_Scalar.inverse_transform(backtest_forecas
t)
```

In [53]:
```
true_back_forecast
```

Out[53]:
```
array([[2805.86080238],
       [2775.69666043],
       [2758.60942103],
       [2726.67421244],
       [2696.23810433]])
```

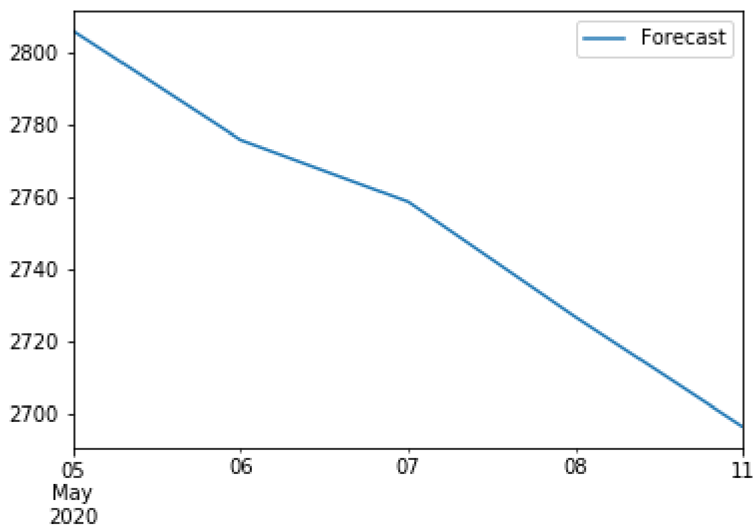
Back Forecast TIme series

In [54]:
```
forecast_date_time = pd.date_range(start = "2020-05-5", periods=perio, freq="B")
```

In [55]:
```
back_df = pd.DataFrame(true_back_forecast, index=forecast_date_time, columns=["Forecast"])
```

In [56]:
```
back_df.plot()
```

Out[56]: <matplotlib.axes._subplots.AxesSubplot at 0x7fda10061210>



Model Prediction

In [57]:
```
back_df.head(1)
```

Out[57]:

	Forecast
2020-05-05	2805.860802

True value on that Date

In [58]:
```
data.loc["2020-5-5"]
```

Out[58]:
```
Adj Close    2868.439941
Name: 2020-05-05 00:00:00, dtype: float64
```

In [ ]:
```

```