CUNY MSDS DATA618 - Quantative Finance

Week 10 : Brain Stumper 6

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1. Source a year's data leading up to the peak shown for each of the indices and run your Kalman filter routine to test its limits as a predictive tool of future market behavior.

Definitions

Kalman Filter: The Kalman Filter, also known as 'Linear Quadratic Estimation (LQE)', is an algorithm that uses a series of measurements observed over time, including noise and inaccuracies, to produce estimates of unknown variables.

We'll import the libraries that we will use:

In [1]:
```
from pykalman import KalmanFilter
import numpy as np
import pandas as pd
import datetime
from pandas_datareader import data as pdr

import matplotlib.pyplot as plt
%matplotlib inline

import pylab as pl
```

Below we will load stock data from 'Nasdaq'. We will use the date range "2006-10-31 to 2007-10-31" to apply the Kalman Filter, and "2007-10-25 to 2007-11-16" as the data to reference for our predictions.

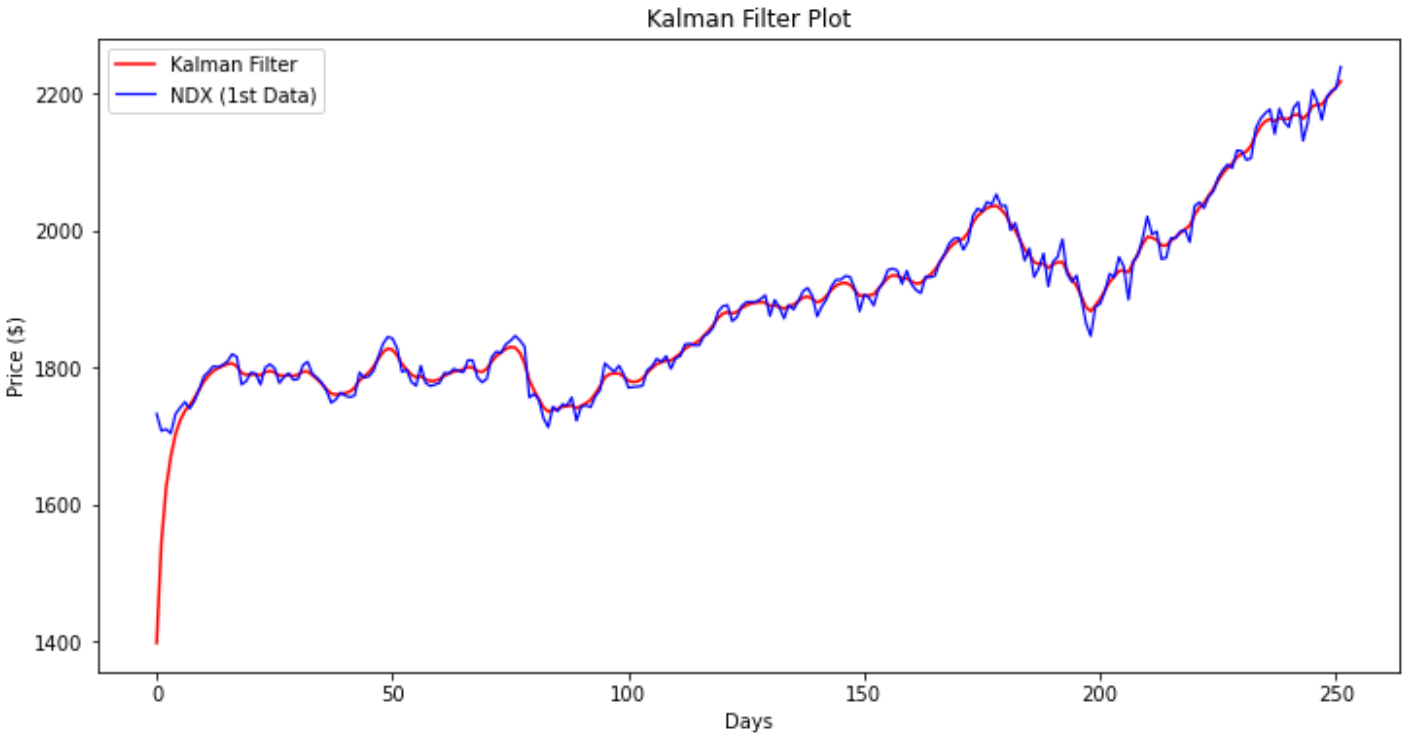
In [2]:
```
start = datetime.datetime(2006, 10, 31)
end = datetime.datetime(2007, 10, 31)

start2 = datetime.datetime(2007, 10, 25)
end2 = datetime.datetime(2007, 11, 16)

ticker = ['^NDX']

data = pdr.get_data_yahoo(ticker, start, end)['Close']
data2 = pdr.get_data_yahoo(ticker, start2, end2)['Close']
```

Here we will apply a fairly simple Kalman Filter to our first data, which has been loaded from the 'pykalman' package. We define a few parameters in order to fine-tune our filter.

In [3]:
```
kf = KalmanFilter(transition_matrices = [1],
                  observation_matrices = [1],
                  initial_state_mean = 0,
                  initial_state_covariance = 1,
                  observation_covariance = 0.5,
                  transition_covariance = 0.2,
                  n_dim_obs=1)
mean, cov = kf.smooth(data['^NDX'].values)
#mean, std = mean.squeeze(), np.std(cov.squeeze())
plt.figure(figsize=(12,6))
plt.plot(mean, 'red', lw=1.5, label='Kalman Filter')
plt.plot(data['^NDX'].values, 'blue', lw=1.2, label='NDX (1st Data)')
```

```
plt.legend()
plt.title("Kalman Filter Plot")
plt.ylabel("Price ($)")
plt.xlabel("Days")
```

Out[3]:
```
Text(0.5, 0, 'Days')
```



Now, we will use the filter with the second data in order to predict future values and make a quick comparison.

In [4]:
```
predict = kf.em(data['^NDX'].values).smooth(data2['^NDX'].values)[0]
predict = pd.DataFrame(predict)
```

As we can observe below, the predictions seem to be very close to the actual values from the second data.

In [5]:
```
data2['Predictions'] = predict.values
data2
```

Out[5]:

Symbols	^NDX	Predictions
Date		
2007-10-25	2161.520020	1399.599255
2007-10-26	2194.590088	1816.267801
2007-10-29	2203.419922	2020.033037
2007-10-30	2207.610107	2120.596118
2007-10-31	2238.979980	2172.191514
2007-11-01	2197.070068	2186.201270
2007-11-02	2213.860107	2194.094538
2007-11-05	2200.479980	2190.864605
2007-11-06	2223.969971	2182.223558
2007-11-07	2169.429932	2150.089447

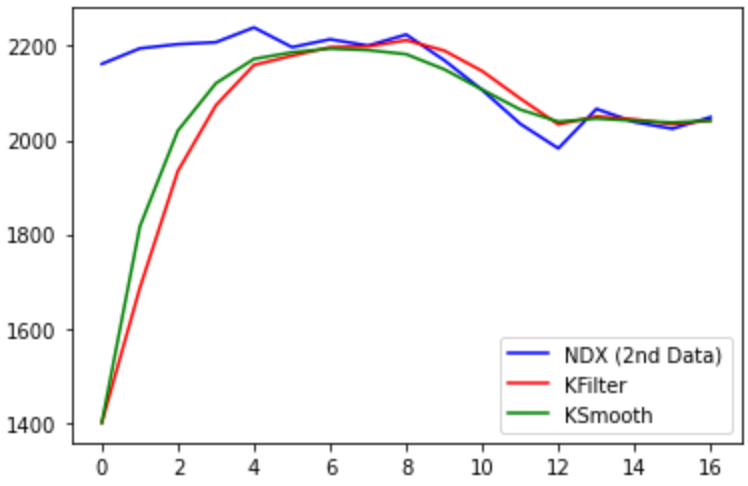
Symbols	^NDX	Predictions
Date		
2007-11-08	2106.159912	2107.071353
2007-11-09	2034.300049	2064.566179
2007-11-12	1982.160034	2039.093466
2007-11-13	2066.080078	2045.660409
2007-11-14	2038.050049	2040.736050
2007-11-15	2024.030029	2037.323257
2007-11-16	2048.620117	2041.391313

Lastly, below we have created a plot of the Kalman Filter and Kalman Smooth from the 'pykalman' package, against our second data. We can observe how both the Filter and the Smooth closely estimate the values of the data set, but there is a dip in the index that may not have been estimated perfectly.

This could represent a missed opportunity as we did not get accurate estimates.

In [6]:
```
smoothed_state_estimates = kf.smooth(data2['^NDX'])[0]
filtered_state_estimates = kf.filter(data2['^NDX'])[0]
```

In [7]:
```
pl.figure()
lines_true = pl.plot(data2['^NDX'].values, color='b')
lines_filt = pl.plot(filtered_state_estimates, color='r')
lines_smooth = pl.plot(smoothed_state_estimates, color='g')
pl.legend((lines_true[0], lines_filt[0], lines_smooth[0]),
          ('NDX (2nd Data)', 'KFilter', 'KSmooth'),
          loc='lower right'
)
pl.show()
```



Below we will continue with the analysis for the Dow Jones and S&P 500 indices.

In [8]:
```
dj_start = datetime.datetime(2006, 10, 9)
dj_end = datetime.datetime(2007, 10, 9)

dj_start2 = datetime.datetime(2007, 10, 3)
dj_end2 = datetime.datetime(2007, 10, 25)

dj_ticker = ['^DJI']
```

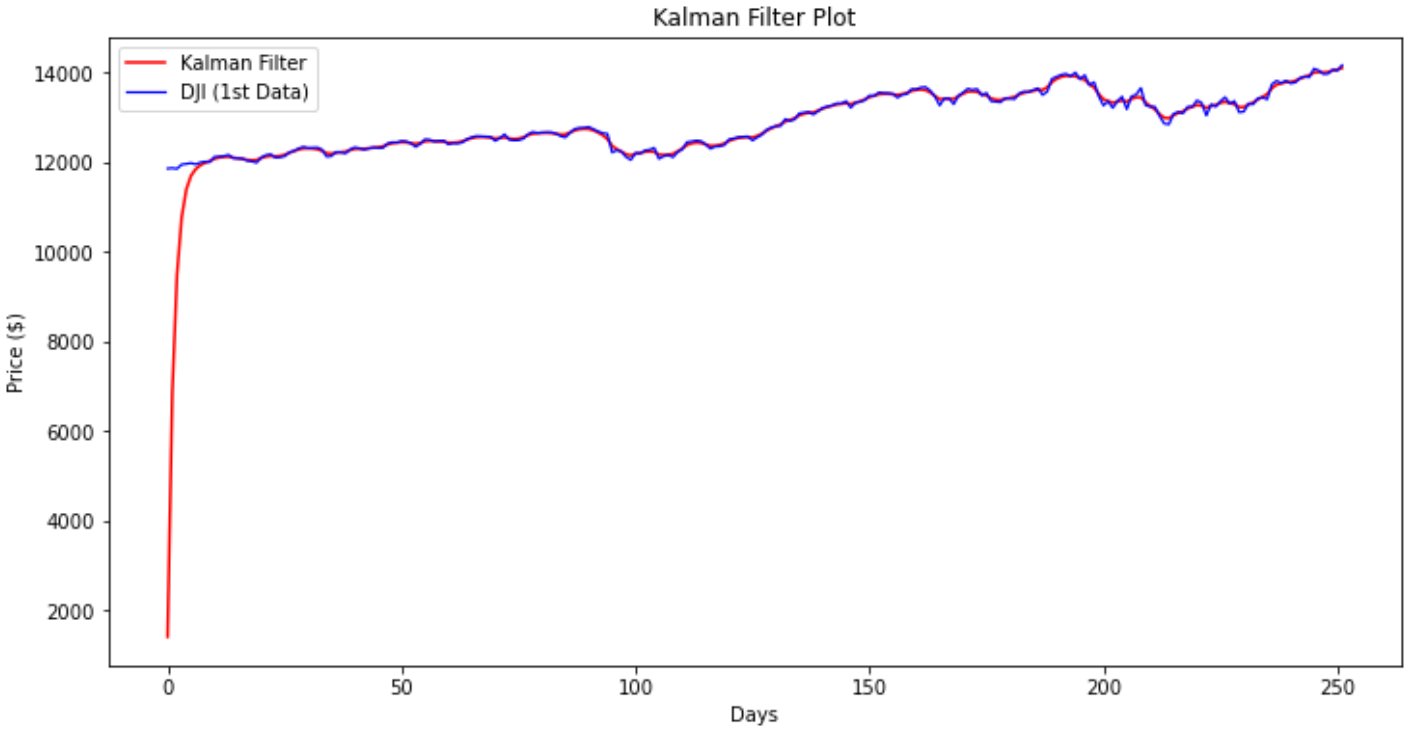
```
dj_data = pdr.get_data_yahoo(dj_ticker, dj_start, dj_end)['Close']
dj_data2 = pdr.get_data_yahoo(dj_ticker, dj_start2, dj_end2)['Close']
```

In [9]:

```
mean, cov = kf.smooth(dj_data['^DJI'].values)
#mean, std = mean.squeeze(), np.std(cov.squeeze())
plt.figure(figsize=(12,6))
plt.plot(mean, 'red', lw=1.5, label='Kalman Filter')
plt.plot(dj_data['^DJI'].values, 'blue', lw=1.2, label='DJI (1st Data)')
plt.legend()
plt.title("Kalman Filter Plot")
plt.ylabel("Price ($)")
plt.xlabel("Days")
```

Out[9]:

```
Text(0.5, 0, 'Days')
```



In [10]:

```
dj_predict = kf.em(dj_data['^DJI'].values).smooth(dj_data2['^DJI'].values)[0]
dj_predict = pd.DataFrame(dj_predict)
```

In [11]:

```
dj_data2['Predictions'] = dj_predict.values
dj_data2
```

Out[11]:

Symbols	^DJI	Predictions
Date		
2007-10-03	13968.049805	1403.152874
2007-10-04	13974.309570	7701.219728
2007-10-05	14066.009766	10879.871108
2007-10-08	14043.730469	12474.153304
2007-10-09	14164.530273	13287.932842
2007-10-10	14078.690430	13665.807322
2007-10-11	14015.120117	13838.367676

Symbols	^DJI	Predictions
Date		
2007-10-12	14093.080078	13923.034454
2007-10-15	13984.799805	13923.142750
2007-10-16	13912.940430	13892.590882
2007-10-17	13892.540039	13851.919807
2007-10-18	13888.959961	13791.049534
2007-10-19	13522.019531	13681.491404
2007-10-22	13566.969727	13651.233753
2007-10-23	13676.230469	13662.878023
2007-10-24	13675.250000	13667.882529
2007-10-25	13671.919922	13669.223418

In [12]:

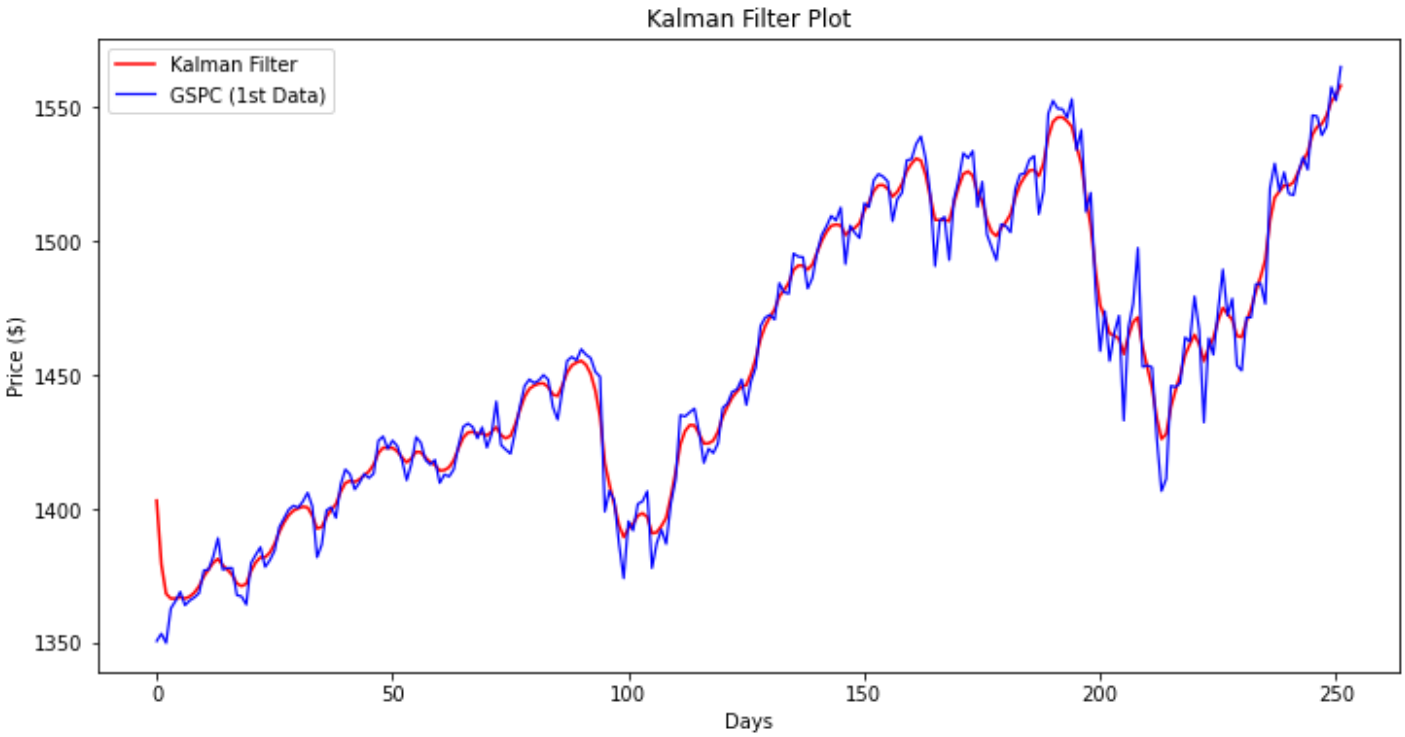
```
sp_start = datetime.datetime(2006, 10, 9)
sp_end = datetime.datetime(2007, 10, 9)

sp_start2 = datetime.datetime(2007, 10, 3)
sp_end2 = datetime.datetime(2007, 10, 25)

sp_ticker = ['^GSPC']

sp_data = pdr.get_data_yahoo(sp_ticker, sp_start, sp_end)['Close']
sp_data2 = pdr.get_data_yahoo(sp_ticker, sp_start2, sp_end2)['Close']
```

In [13]:

```
mean, cov = kf.smooth(sp_data['^GSPC'].values)
#mean, std = mean.squeeze(), np.std(cov.squeeze())
plt.figure(figsize=(12,6))
plt.plot(mean, 'red', lw=1.5, label='Kalman Filter')
plt.plot(sp_data['^GSPC'].values, 'blue', lw=1.2, label='GSPC (1st Data)')
plt.legend()
plt.title("Kalman Filter Plot")
plt.ylabel("Price ($)")
plt.xlabel("Days")
```

Out[13]:

```
Text(0.5, 0, 'Days')
```



In [14]:
```
sp_predict = kf.em(sp_data['^GSPC'].values).smooth(sp_data2['^GSPC'].values)[0]
sp_predict = pd.DataFrame(sp_predict)
```

In [15]:
```
sp_data2['Predictions'] = sp_predict.values
sp_data2
```

Out[15]:

Symbols	^GSPC	Predictions
Date		
2007-10-03	1539.589966	1403.190588
2007-10-04	1542.839966	1499.459669
2007-10-05	1557.589966	1537.901368
2007-10-08	1552.579956	1550.097507
2007-10-09	1565.150024	1558.984460
2007-10-10	1562.469971	1559.652510
2007-10-11	1554.410034	1556.564790
2007-10-12	1561.800049	1556.349432
2007-10-15	1548.709961	1548.868220
2007-10-16	1538.530029	1541.597972
2007-10-17	1541.239990	1538.417395
2007-10-18	1540.079956	1531.474204
2007-10-19	1500.630005	1513.059259
2007-10-22	1506.329956	1511.212923
2007-10-23	1519.589966	1515.875745
2007-10-24	1515.880005	1515.587387

Symbols	^GSPC	Predictions
Date		
2007-10-25	1514.400024	1514.908960

In the predictions of both the Dow Jones and the S&P 500 we can observe how the estimates keep increasing past the peak date of October 9, 2007. This was also the case in the predictions for Nasdaq, the estimates kept increasing past the peak and if we were to invest based on these estimates, we would be overvaluing the stock price.

In [ ]: