JP Morgan Mini Project 1

In [1]:
```python
import pandas as pd
import math
import operator
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
plt.style.use("ggplot")
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima_model import ARIMA
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```python
# loading dataset
nifty = pd.read_csv("NIFTY.csv")
nifty.index = pd.to_datetime(nifty.Date)
nifty.describe()
```

Out[2]:

	Open	High	Low	Close
count	250.000000	250.000000	250.000000	250.000000
mean	13367.213404	13435.472791	13261.676603	13355.313385
std	1706.866327	1713.182699	1694.558284	1706.141755
min	10323.799810	10401.049810	10267.349610	10302.099610
25%	11539.587890	11584.312257	11454.687260	11523.212408
50%	13761.500000	13831.399905	13660.174805	13754.899905
75%	14834.162603	14917.262700	14704.262452	14849.337402
max	15915.349610	15915.650390	15842.400390	15869.250000

In [3]:
```python
# loading dataset
sgx_nifty = pd.read_csv("SGX Nifty.csv")
sgx_nifty.index = pd.to_datetime(sgx_nifty.Date)
sgx_nifty.describe()
```

Out[3]:

	Open	High	Low	Close
count	250.000000	250.000000	250.000000	250.000000
mean	2051.822601	2075.947193	2022.966408	2047.625007
std	124.753095	125.641820	122.249624	122.931349
min	1720.000000	1741.000000	1695.550049	1704.099976
25%	1959.399994	1977.450012	1932.000000	1956.375030
50%	2031.750000	2060.575074	2000.625000	2028.024964
75%	2140.762512	2166.500000	2105.500000	2134.025086
max	2325.000000	2369.350098	2310.550049	2324.550049

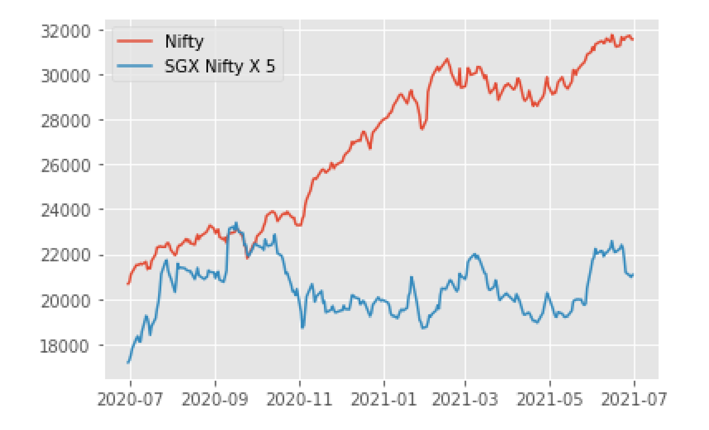
Attempt 1 using Regression on prices:

Let nifty = f(sgx_nifty). In this attempt, the aim is to find the function f and then using assumption that Inda.P and Nifty are related in the same way as Nifty and SGX Nifty, we get Inda.P=f(nifty)

In [4]:
```python
#Calculating mid value
nifty["Mid"]=nifty["High"]+nifty["Low"]
sgx_nifty["Mid"]=sgx_nifty["High"]+sgx_nifty["Low"]
```

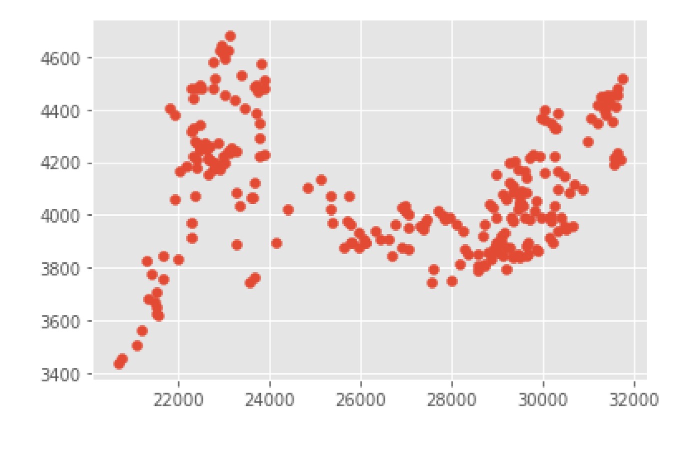
In [5]:
```python
plt.plot(nifty.index, nifty["Mid"])
plt.plot(sgx_nifty.index, sgx_nifty["Mid"]*5)

plt.legend(["Nifty", "SGX Nifty X 5"])
```

Out[5]: <matplotlib.legend.Legend at 0x1e2246ea188>



In [6]:
```python
plt.scatter(nifty["Mid"],sgx_nifty["Mid"] )
```

Out[6]: <matplotlib.collections.PathCollection at 0x1e2268645c8>

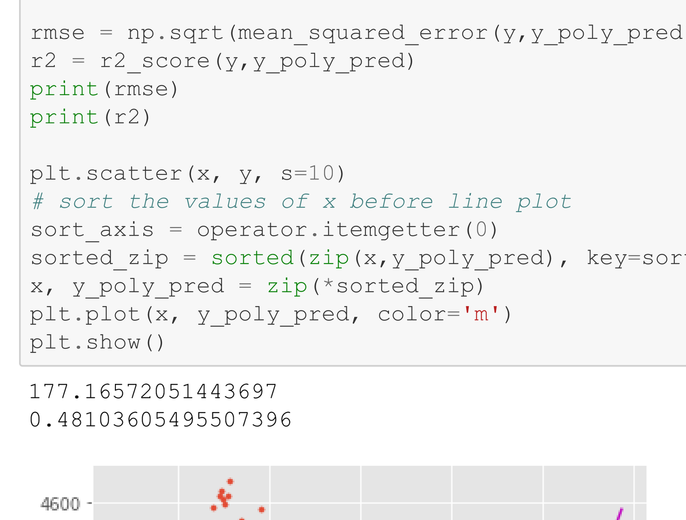


Aim: To find relation between nifty and sgx nifty
Based on above plot, it looked like a cubic function would be a better fit. sgx_nifty=f(nifty) where, f can be a cubic function

Cubic regression

In [7]:
```python
polynomial_features= PolynomialFeatures(degree=3)
x=nifty["Mid"]
x = x[:, np.newaxis]

x_poly = polynomial_features.fit_transform(x)
model = LinearRegression()
y=sgx_nifty["Mid"]
y = y[:, np.newaxis]
model.fit(x_poly,y )
y_poly_pred = model.predict(x_poly)

rmse = np.sqrt(mean_squared_error(y,y_poly_pred))
r2 = r2_score(y,y_poly_pred)
print(rmse)
print(r2)

plt.scatter(x, y, s=10)
# sort the values of x before line plot
sort_axis = operator.itemgetter(0)
sorted_zip = sorted(zip(x,y_poly_pred), key=sort_axis)
x, y_poly_pred = zip(*sorted_zip)
plt.plot(x, y_poly_pred, color='m')
plt.show()
```

```
177.16572051443697
0.48103605495507396
```

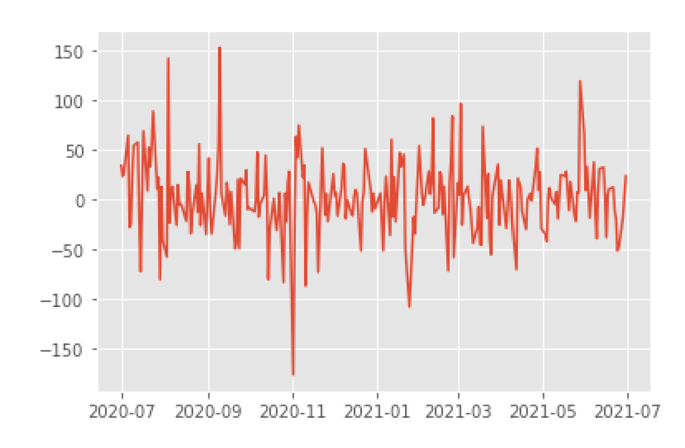


- From the above plot, sgx_nifty can be modelled approximately to a cubic function of nifty. Since above cubic function is not monotonic, we cannot find function f in this case.
- Instead of cubic function, we can model nifty as linear function of sgx_nifty, but clearly from the above scatter plot, linear function would not be a good fit.

Approach 2 using Regression for Daily Price Change:

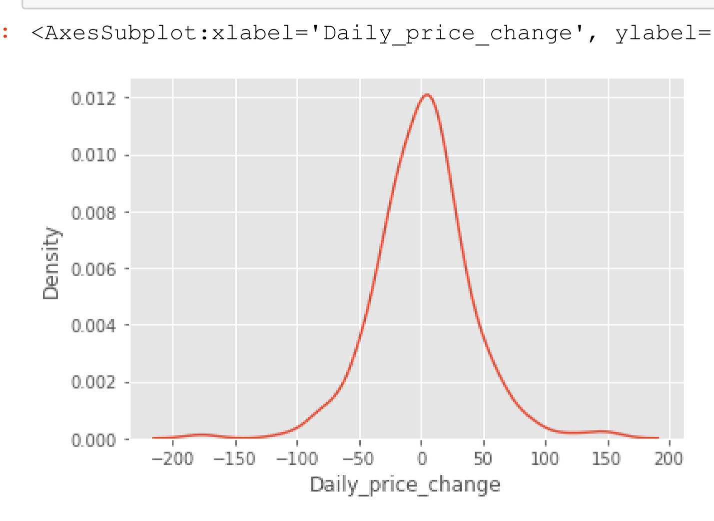
In [8]:
```python
sgx_nifty["Daily_price_change"]=sgx_nifty["Close"].diff(periods=1)
plt.plot(sgx_nifty.index, sgx_nifty["Daily_price_change"])
```

Out[8]: [<matplotlib.lines.Line2D at 0x1e228992308>]



In [9]:
```python
sns.kdeplot(data=sgx_nifty, x="Daily_price_change")
```

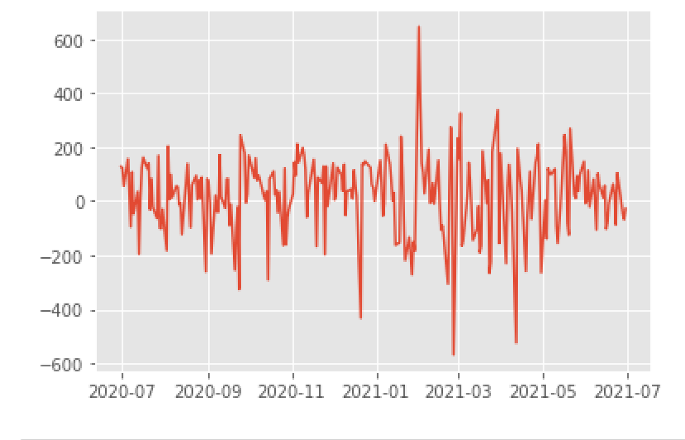
Out[9]: <AxesSubplot:xlabel='Daily_price_change', ylabel='Density'>



From the above plot it can be confirmed that Daily Change in Price for sgx_nifty approximately follows Gaussian Distribution.

In [10]:
```python
nifty["Daily_price_change"]=nifty["Close"].diff(periods=1)
plt.plot(nifty.index, nifty["Daily_price_change"])
```

Out[10]: [<matplotlib.lines.Line2D at 0x1e228981688>]



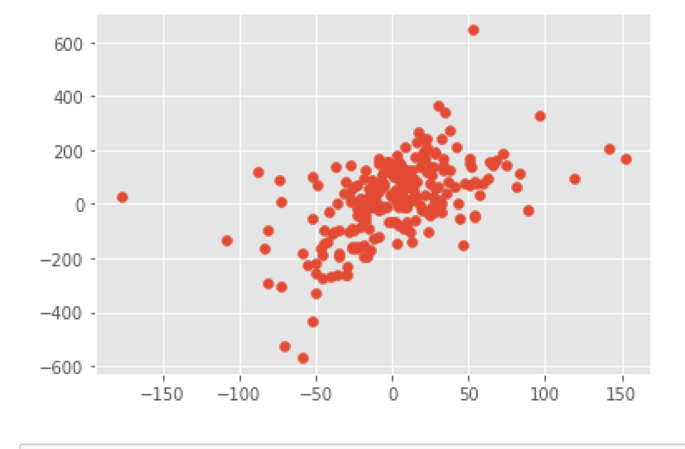
In [11]:
```python
sns.kdeplot(data=nifty, x="Daily_price_change")
```

Out[11]: <AxesSubplot:xlabel='Daily_price_change', ylabel='Density'>

The plot for Daily Change in Price for nifty is a bit skewed towards the left.

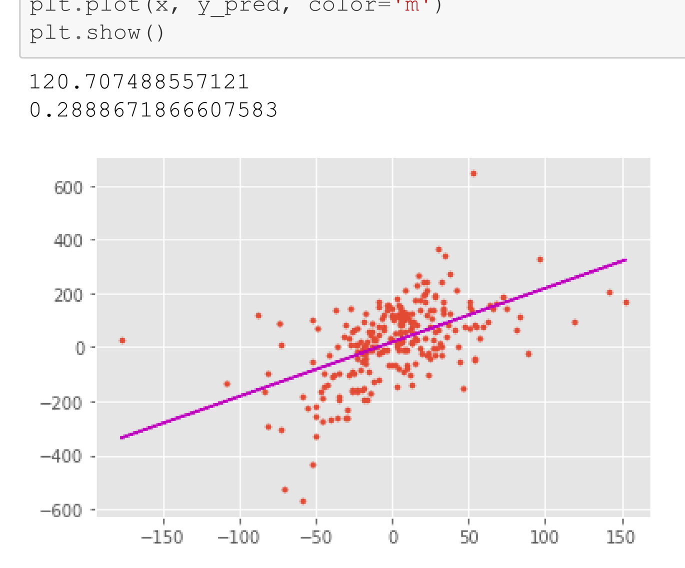
In [19]:
```python
plt.scatter(sgx_nifty["Daily_price_change"],nifty["Daily_price_change"] )
```

Out[19]: <matplotlib.collections.PathCollection at 0x1e228c51888>

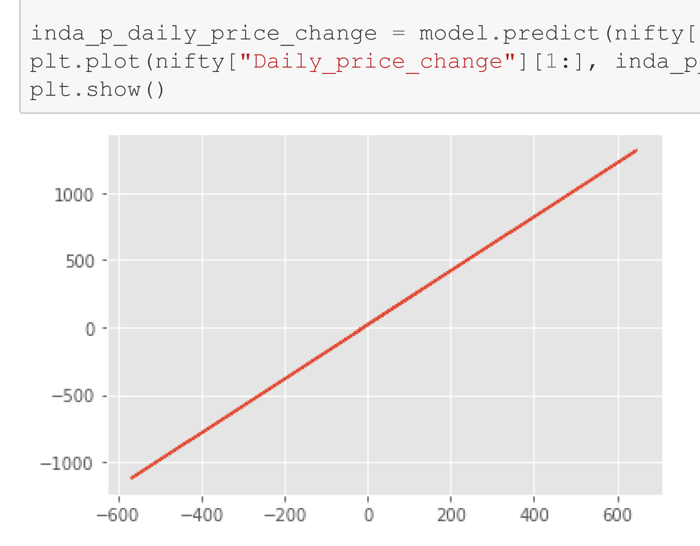


In [23]:
```python
model = LinearRegression()
x=sgx_nifty[["Daily_price_change"]][1:]
y=nifty["Daily_price_change"][1:]
model.fit(x,y )
y_pred = model.predict(x)

rmse = np.sqrt(mean_squared_error(y,y_pred))
r2 = r2_score(y,y_pred)
print(rmse)
print(r2)

plt.scatter(x, y, s=10)

plt.plot(x, y_pred, color='m')
plt.show()
```

```
120.707488557121
0.2888671866607583
```



In [24]:
```python
#Use the above model with x as nifty and y as inda.p

inda_p_daily_price_change = model.predict(nifty[["Daily_price_change"]][1:])
plt.plot(nifty["Daily_price_change"][1:], inda_p_daily_price_change)
plt.show()
```



In [25]:
```python
# Standard deviation of inda.p
inda_p_daily_price_change.std()
```

Out[25]: 286.7060524084118

- This approach cannot be used as the given standard deviation (i.e) 1.65(see next approach) is very different from the above value.
- Also this is change in daily price which is even larger than closing price (i.e)USD 110

Approach 3 using Standard deviation and Correlation:

Q1

- **Assumption:** Inda.P and Nifty have same correlation as Nifty and SGX Nifty = rho
- **Given:**
  - Standard Deviation for Inda.P returns = 1.5 x 0.01
  - Closing price at 30th June 2021 = USD 110
- **Approach:**
  - Find standard deviation of Inda.P Daily Price Change = sigma1 = (standard deviation for returns) x closing_price = 1.5 x 0.01 x 110
  - Find standard deviation of Nifty Daily Price Change = sigma2
  - Calculation rho
  - Covariance of Inda.P and Nifty = rho x sigma1 x sigma2

In [13]:
```python
#Pearson correlation for Nifty and SGX Nifty
rho=nifty["Daily_price_change"][1:].corr(sgx_nifty["Daily_price_change"][1:])
rho
```

Out[13]: 0.5374636607815992

In [14]:
```python
#Standard deviation of Inda.P Daily Price Change (i.e) sigma1
sigma1=1.5*0.01*110
sigma1
```

Out[14]: 1.65

In [15]:
```python
#Standard deviation of Nifty Daily Price Change (i.e) sigma2
sigma2=nifty["Daily_price_change"].std()
sigma2
```

Out[15]: 143.42758567581095

In [16]:
```python
#Covariance of Inda.P and Nifty
covariance=rho*sigma1*sigma2
covariance
```

Out[16]: 127.19374016973988

Q2

- **Assumptions:**
  - Mean of Daily Price Change for Inda.P is 0
  - Closing Prices is calculated for 1st July 2021
- **Given:**
  - Standard Deviation for Daily Price Change for Inda.P = sigma1 = 1.65
  - Closing price at 30th June 2021 = USD 110
  - z=1.96 for 95% CI
- **Approach:**
  - Calculate Confidence Interval for Daily Price Change of Inda.P using:

$$\mathrm{CI} = \bar{X} \pm (z \times \sigma_{\bar{X}})$$

$$\sigma_{\bar{X}} = \frac{s}{\sqrt{N}}$$

  - Once the confidence interval is found, we can add closing price at 30th June 2021 (i.e) USD 110 to both left and right limits of the interval.

In [17]:
```python
#Confidence interval for daily price change of Inda.P
N=nifty["Daily_price_change"].count()
CI=(1.96*sigma1)/math.sqrt(N)
CI
```

Out[17]: 0.20494642261961615

In [18]:
```python
#Range of Closing prices on 1st July 2021
print("[",110-CI,110+CI,"]")
```

```
[ 109.79505357738039 110.20494642261961 ]
```

In [ ]: