In [311]:

```
import pandas as pd
data = pd.read_csv('GOOGL CSV.csv')
```

In [312]:

```
data
```

Out[312]:

| | Date | Open | High | Low | Close | Adj Close | Volume |
|---|---|---|---|---|---|---|---|
| **0** | 8/19/2004 | 50.050049 | 52.082081 | 48.028027 | 50.220219 | 50.220219 | 44659096 |
| **1** | 8/20/2004 | 50.555557 | 54.594597 | 50.300301 | 54.209209 | 54.209209 | 22834343 |
| **2** | 8/23/2004 | 55.430431 | 56.796799 | 54.579578 | 54.754753 | 54.754753 | 18256126 |
| **3** | 8/24/2004 | 55.675674 | 55.855858 | 51.836838 | 52.487488 | 52.487488 | 15247337 |
| **4** | 8/25/2004 | 52.532532 | 54.054054 | 51.991993 | 53.053055 | 53.053055 | 9188602 |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **4401** | 2/10/2022 | 2794.070068 | 2829.689941 | 2759.139893 | 2772.399902 | 2772.399902 | 1966500 |
| **4402** | 2/11/2022 | 2772.000000 | 2783.129883 | 2668.000000 | 2685.649902 | 2685.649902 | 1994200 |
| **4403** | 2/14/2022 | 2665.129883 | 2726.000000 | 2665.129883 | 2710.520020 | 2710.520020 | 1713900 |
| **4404** | 2/15/2022 | 2751.409912 | 2762.169922 | 2716.429932 | 2732.169922 | 2732.169922 | 1334000 |
| **4405** | 2/16/2022 | 2732.929932 | 2740.610107 | 2700.000000 | 2720.679932 | 2720.679932 | 673361 |

4406 rows × 7 columns

**We can observe that its a time series data**

In [313]:

```
target = data['High']
target.value_counts()
```

Out[313]:

```
950.000000     3
548.000000     3
236.736740     3
195.195190     3
565.000000     3
              ..
229.134140     1
228.858856     1
230.225220     1
230.110107     1
2740.610107    1
Name: High, Length: 4258, dtype: int64
```

In [314]:

```
dataA = data.drop(labels = ['High'],axis = 1)
dataB = data.drop(labels = ['Low'],axis = 1)
```

In [315]:

```
#Checking for duplicates
data.isna().sum()
```

Out[315]:

```
Date          0
```

```
Open          0
High          0
Low           0
Close         0
Adj Close     0
Volume        0
dtype: int64
```

In [316]:

```
#checking correlation btw features
corr = data.corr()
corr.style.background_gradient(cmap='coolwarm')
```

Out[316]:

| | Open | High | Low | Close | Adj Close | Volume |
|---|---|---|---|---|---|---|
| **Open** | 1.000000 | 0.999921 | 0.999905 | 0.999822 | 0.999822 | -0.455981 |
| **High** | 0.999921 | 1.000000 | 0.999880 | 0.999907 | 0.999907 | -0.455030 |
| **Low** | 0.999905 | 0.999880 | 1.000000 | 0.999920 | 0.999920 | -0.457492 |
| **Close** | 0.999822 | 0.999907 | 0.999920 | 1.000000 | 1.000000 | -0.456380 |
| **Adj Close** | 0.999822 | 0.999907 | 0.999920 | 1.000000 | 1.000000 | -0.456380 |
| **Volume** | -0.455981 | -0.455030 | -0.457492 | -0.456380 | -0.456380 | 1.000000 |

**We can observe that Except Volume, all the features are highly correlated**

**Adj Close**

In [317]:

```
import seaborn as sns
import matplotlib.pyplot as plt
```

In [318]:

```
#checking mean , std , min etc
data['Adj Close'].describe()
```

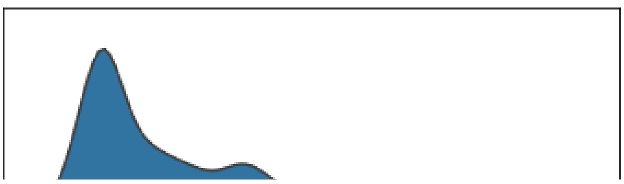
Out[318]:

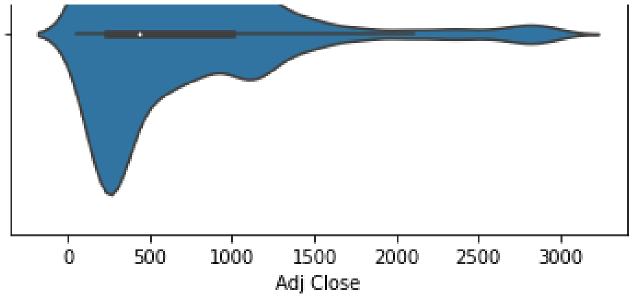
```
count    4406.000000
mean      681.950130
std       629.734137
min        50.055054
25%       247.757752
50%       430.450454
75%       992.279999
max      2996.770020
Name: Adj Close, dtype: float64
```

In [319]:

```
sns.violinplot(data['Adj Close'])
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```






### Close

In [320]:

```
data['Close'].describe()
```

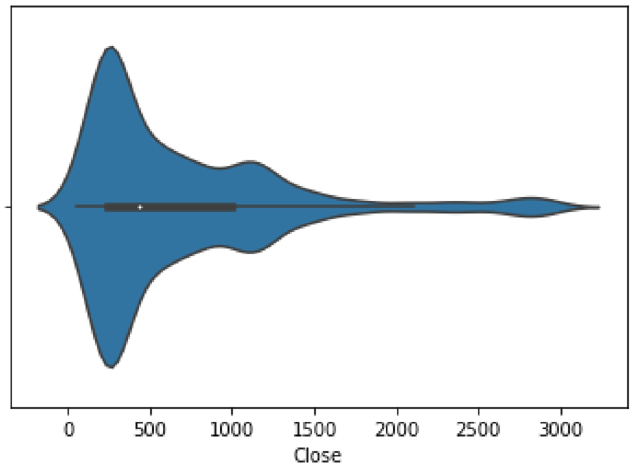
Out[320]:

```
count    4406.000000
mean      681.950130
std       629.734137
min        50.055054
25%       247.757752
50%       430.450454
75%       992.279999
max      2996.770020
Name: Close, dtype: float64
```

In [321]:

```
sns.violinplot(data['Close'])
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```




### Open

In [322]:

```
data['Open'].describe()
```

Out[322]:

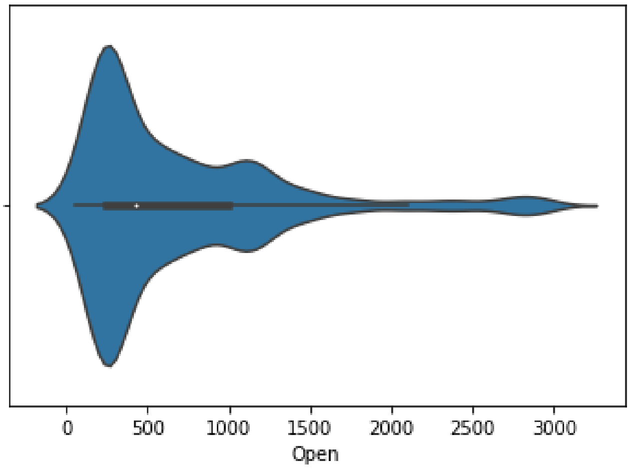
```
count    4406.000000
mean      681.951261
std       629.705043
min        49.644646
25%       247.935428
50%       431.378875
75%       993.699982
```

```
max       3025.000000
Name: Open, dtype: float64
```

In [323]:

```python
sns.violinplot(data['Open'])
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the
following variable as a keyword arg: x. From version 0.12, the only valid positional argu
ment will be `data`, and passing other arguments without an explicit keyword will result
in an error or misinterpretation.
  FutureWarning
```




**Volume**

In [324]:

```python
data['Volume'].describe()
```

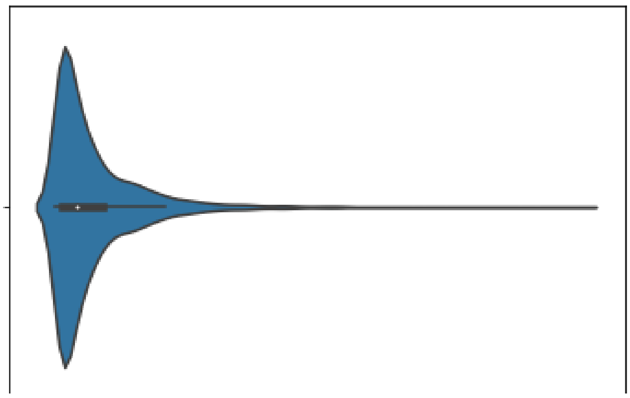
Out[324]:

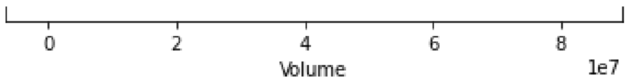
```
count    4.406000e+03
mean     6.471553e+06
std      7.703985e+06
min      4.656000e+05
25%      1.697800e+06
50%      3.803497e+06
75%      8.075466e+06
max      8.215117e+07
Name: Volume, dtype: float64
```

In [325]:

```python
sns.violinplot(data['Volume'])
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the
following variable as a keyword arg: x. From version 0.12, the only valid positional argu
ment will be `data`, and passing other arguments without an explicit keyword will result
in an error or misinterpretation.
  FutureWarning
```






**Volume feature has wide range**

**Date Feature**

In [326]:

```
import regex as re
#transforming feature
data['Date']
date = [i.split('/') for i in data['Date']]
data['MM'] = [i[0] for i in date]
data['DD'] = [i[1] for i in date]
data['YYYY'] = [i[2] for i in date]
```

In [327]:

```
data = data.drop(labels=['Date'],axis=1)
```

In [328]:

```
dataA = data.drop(labels = ['High'],axis = 1)
dataB = data.drop(labels = ['Low'],axis = 1)
targetA = data['High']
targetB = data['Low']
```

In [329]:

```
from sklearn.model_selection import train_test_split
trainA = dataA.iloc[0:3000,:]
testA = dataA.iloc[3000:,:]
y_trainA = targetA[0:3000]
y_testA = targetA[3000:]

trainB = dataB.iloc[0:3000,:]
testB = dataB.iloc[3000:,:]
y_trainB = targetB[0:3000]
y_testB = targetB[3000:]
```

**LinearRegression**

**Set A - predicting High Value**

In [330]:

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import accuracy_score
model = LinearRegression()
model.fit(trainA,y_trainA)
y_testA_pred = model.predict(testA)
print(type(y_testA_pred))
print(len(y_testA))
```

```
<class 'numpy.ndarray'>
1406
```

In [331]:

```
# MSE
y_testA = list(y_testA)
sum = 0
for i in range(len(y_testA)):
```

```
  sum+=(y_testA[i]-y_testA_pred[i])**2
MSE = 1/len(y_testA)*(sum)

print('MSE setA:',MSE)
```

```
MSE setA: 84.24376060304019
```

#### SetB - Predicting Low Value

In [332]:

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import accuracy_score
model = LinearRegression()
model.fit(trainB,y_trainB)
y_testB_pred = model.predict(testB)
print(type(y_testB_pred))
print(len(y_testB))

# MSE
y_testB = list(y_testB)
sum = 0
for i in range(len(y_testB)):
  sum+=(y_testB[i]-y_testB_pred[i])**2
MSE = 1/len(y_testB)*(sum)

print('MSE setB :',MSE)
```

```
<class 'numpy.ndarray'>
1406
MSE setB : 76.29541241699177
```

#### Random Forest

#### setA

In [333]:

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestRegressor
model = RandomForestRegressor()
model.fit(trainA,y_trainA)
y_testA_pred = model.predict(testA)
#print(type(y_testA_pred))
#print(len(y_testA))

# MSE
y_testA = list(y_testA)
sum = 0
for i in range(len(y_testA)):
  sum+=(y_testA[i]-y_testA_pred[i])**2
MSE = 1/len(y_testA)*(sum)

print('MSE setA Random Forest:',MSE)
```

```
MSE setA Random Forest: 785325.8401205895
```

#### setB

In [334]:

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import accuracy_score
model = RandomForestRegressor()
model.fit(trainB,y_trainA)
y_testB_pred = model.predict(testB)

# MSE
```

```
y_testB = list(y_testB)
sum = 0
for i in range(len(y_testB)):
  sum+=(y_testB[i]-y_testB_pred[i])**2
MSE = 1/len(y_testB)*(sum)

print('MSE setB :',MSE)
```

```
MSE setB : 734775.9332816395
```

**Lets improve Linear Regression Model**

**Feature Engineering**

In [335]:

```
import numpy as np
def split_features(column):
  a = [np.round(i) for i in column]
  b = [i%np.floor(i) for i in column]
  return a,b
```

In [336]:

```
dataA = data.drop(labels = ['High'],axis = 1)
dataB = data.drop(labels = ['Low'],axis = 1)
targetA = data['High']
targetB = data['Low']
```

In [337]:

```
openA , openB = split_features(data['Open'])
highA , highB = split_features(data['High'])
lowA , lowB = split_features(data['Low'])
closeA,closeB = split_features(data['Close'])
adjA , adjB = split_features(data['Adj Close'])
```

In [338]:

```
data['openA'],data['openB'] = openA , openB
data['highA'],data['highB'] = highA , highB
data['lowA'],data['lowB'] = lowA , lowB
data['closeA'],data['closeB'] = closeA , closeB
data['adjA'] , data['adjB'] = adjA , adjB
```

In [339]:

```
df = data.drop(labels = ['Open','High','Low','Close','Adj Close'], axis = True)
```

In [340]:

```
dataA = df.drop(labels = ['highA','highB'],axis = 1)
dataB = df.drop(labels = ['lowA','lowB'],axis = 1)
targetA = data['High']
targetB = data['Low']
```

In [341]:

```
from sklearn.model_selection import train_test_split
trainA = dataA.iloc[0:3000,:]
testA = dataA.iloc[3000:,:]
y_trainA = targetA[0:3000]
y_testA = targetA[3000:]

trainB = dataB.iloc[0:3000,:]
testB = dataB.iloc[3000:,:]
y_trainB = targetB[0:3000]
y_testB = targetB[3000:]
```

### Linear Regression

#### setA

In [342]:

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import accuracy_score
model = LinearRegression()
model.fit(trainA,y_trainA)
y_testA_pred = model.predict(testA)
print(type(y_testA_pred))
print(len(y_testA))

# MSE
y_testA = list(y_testA)
sum = 0
for i in range(len(y_testA)):
  sum+=(y_testA[i]-y_testA_pred[i])**2
MSE = 1/len(y_testA)*(sum)

print('MSE setA:',MSE)
```

```
<class 'numpy.ndarray'>
1406
MSE setA: 84.63234453721245
```

In [343]:

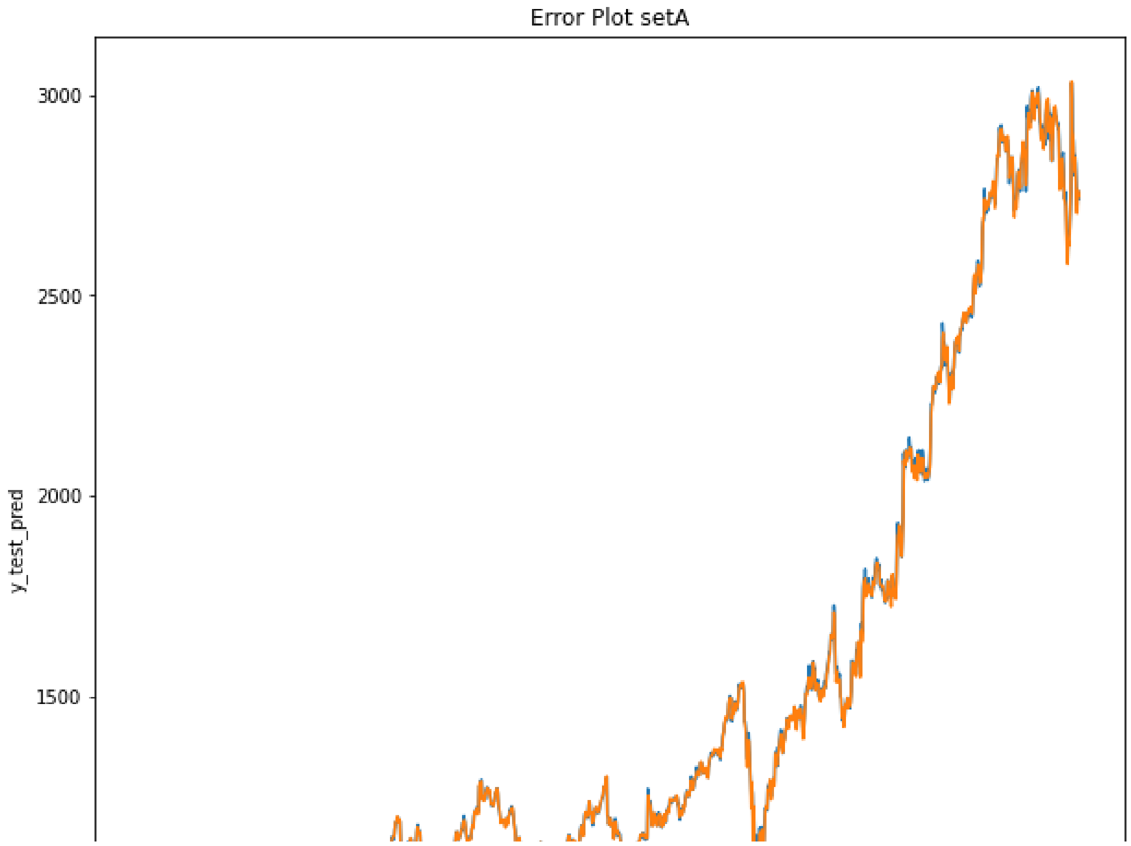
```
error = y_testA - y_testA_pred
```

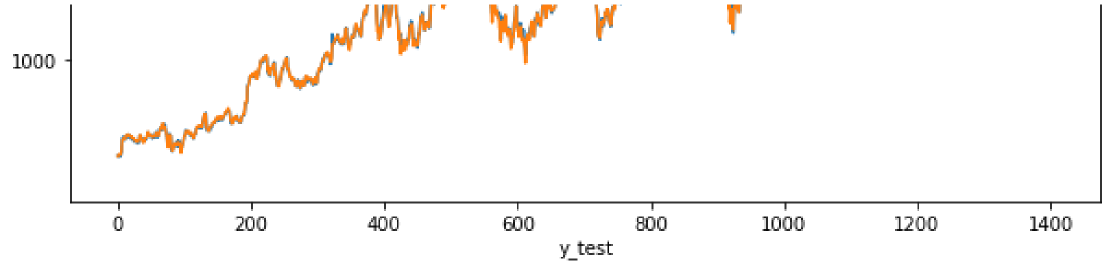
In [349]:

```
plt.figure(figsize=(10,10))
plt.plot(y_testA)
plt.plot(y_testA_pred)
plt.title('Error Plot setA')
plt.xlabel('y_test')
plt.ylabel('y_test_pred')
```

Out[349]:

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






### setB

In [350]:

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import accuracy_score
model = LinearRegression()
model.fit(trainB,y_trainB)
y_testB_pred = model.predict(testB)
print(type(y_testB_pred))
print(len(y_testB))

# MSE
y_testB = list(y_testB)
sum = 0
for i in range(len(y_testB)):
  sum+=(y_testB[i]-y_testB_pred[i])**2
MSE = 1/len(y_testB)*(sum)

print('MSE setB :',MSE)
```

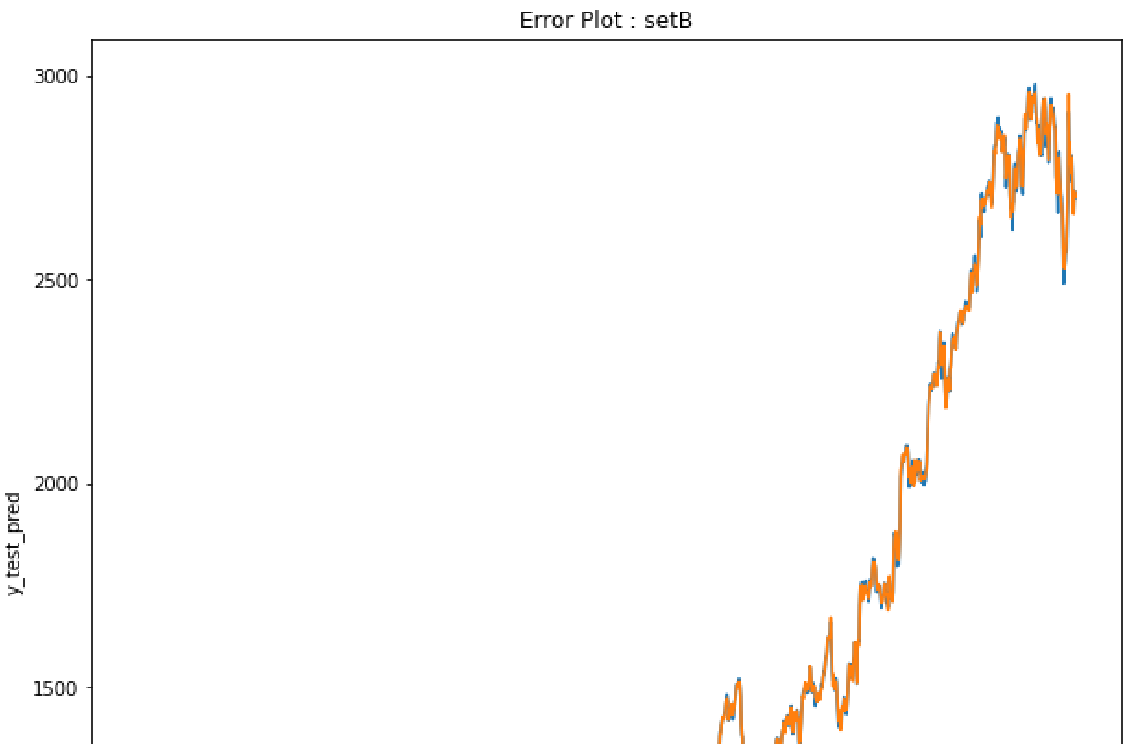
```
<class 'numpy.ndarray'>
1406
MSE setB : 76.3784144062654
```

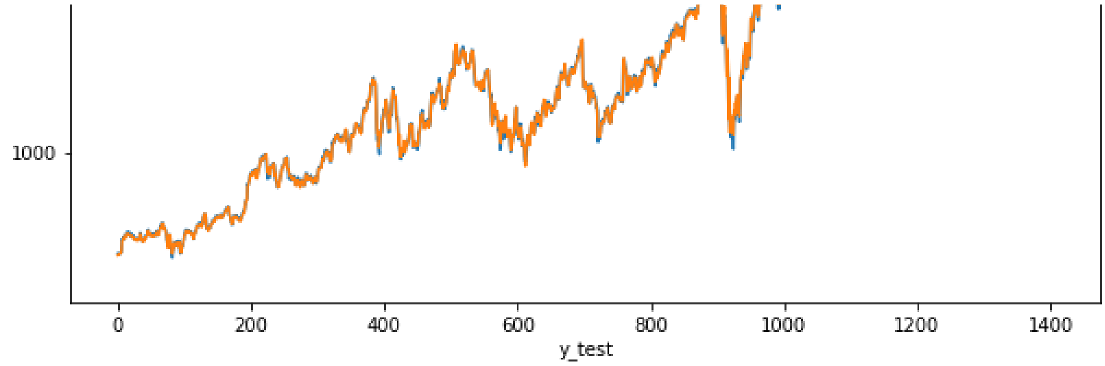
In [352]:

```
plt.figure(figsize=(10,10))
plt.plot(y_testB)
plt.plot(y_testB_pred)
plt.title('Error Plot : setB')
plt.xlabel('y_test')
plt.ylabel('y_test_pred')
```

Out[352]:

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



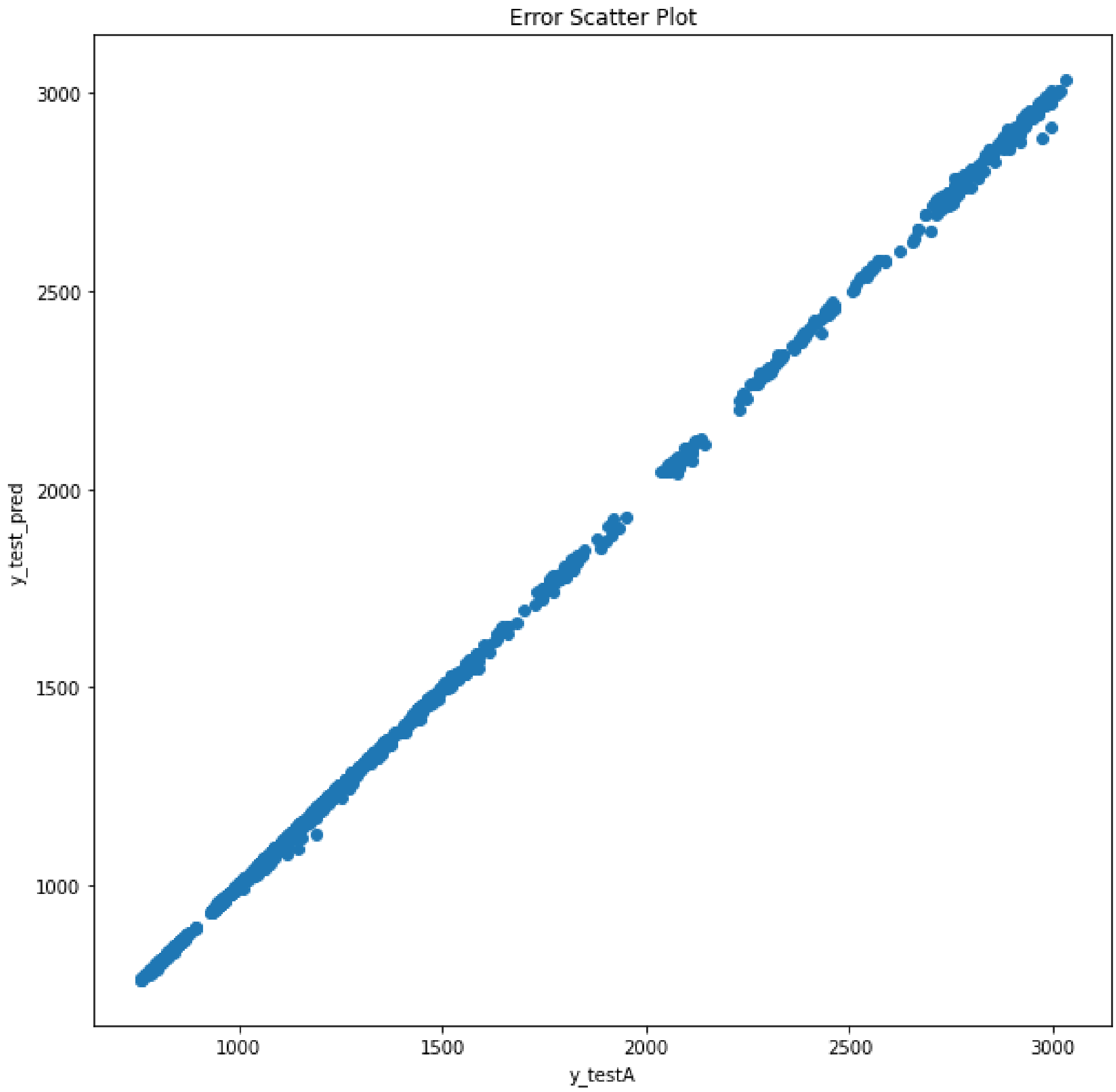



In [354]:

```
plt.figure(figsize=(10,10))
plt.title('Error Scatter Plot')
plt.scatter(y_testA,y_testA_pred)
plt.xlabel('y_testA')
plt.ylabel('y_test_pred')
```

Out[354]:

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

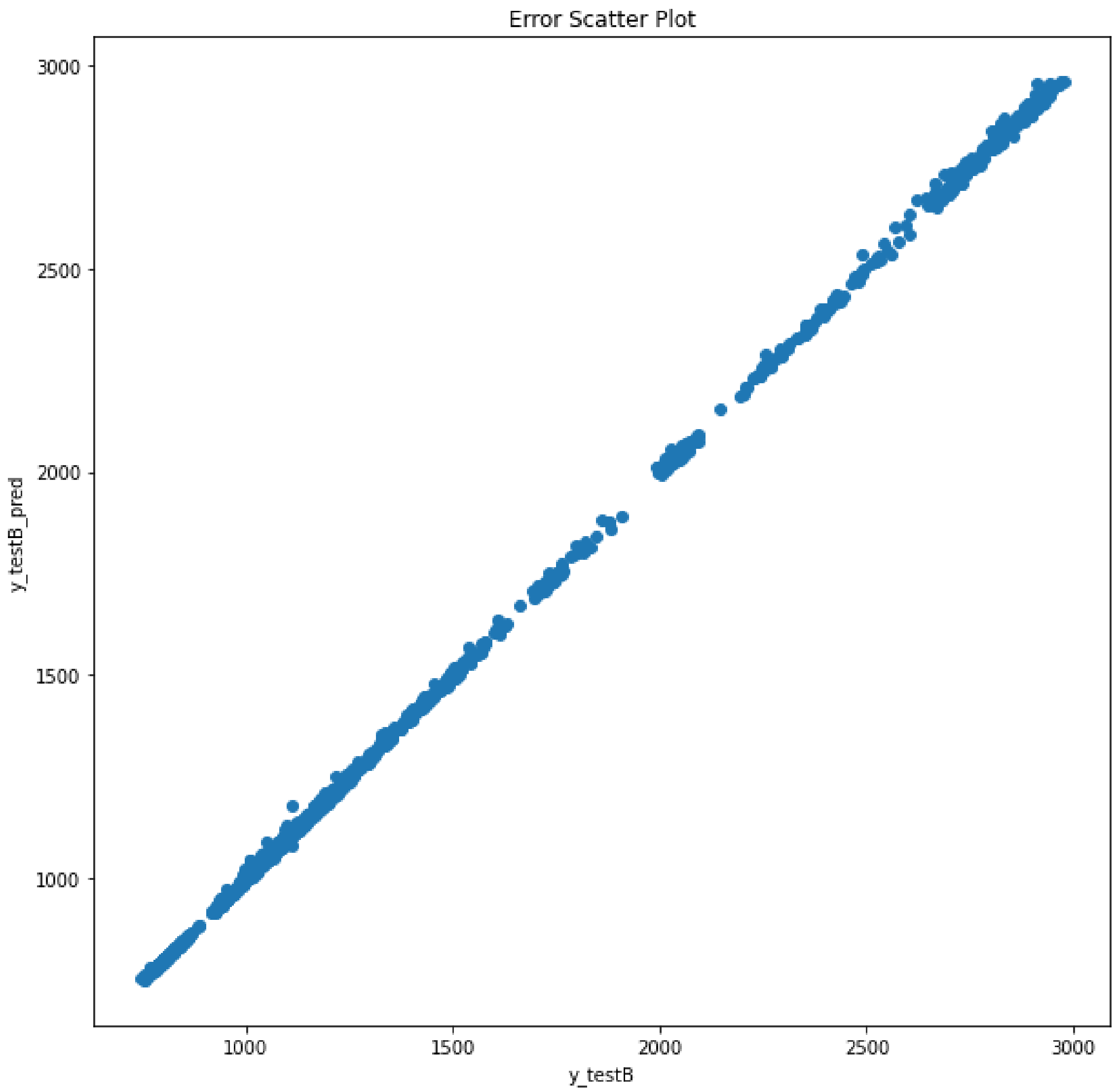



In [355]:

```
plt.figure(figsize=(10,10))
plt.title('Error Scatter Plot')
plt.scatter(y_testB,y_testB_pred)
plt.xlabel('y_testB')
plt.ylabel('y_testB_pred')
```

Out[355]:

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




**Feature Engineering**

In [356]:

```
df['Volume_log'] = df['Volume'].apply(lambda x:np.log(x))
```

**Adding Date Feature**

In [358]:

```
#we can see that the date starts from 19th August 2004,
# ie Thursday , we can label the data using this Day information

#  0 - thursday , 1- friday , 2 - saturday, 3 - sunday , 4- monday , 5 - tuesday , 6 - w
ednesday ,
day = []
cnt = 0
j = 0
for i in range(len(df)):
  day.append(j)
  j+=1
  cnt+=1
  if cnt == 7:
    j = 0
    cnt = 0

df['Day'] = day
```

**Rounding decimal value by 2**

In [359]:

```
df['lowB'] = np.round(df['lowB'],2)
df['highB'] = np.round(df['highB'],2)
df['openB'] = np.round(df['openB'],2)
df['adjB'] = np.round(df['adjB'],2)
df['closeB'] = np.round(df['closeB'],2)
df['Volume_log'] = np.round(df['Volume_log'],2)
```

In [360]:

```
df['V1'] = df['Volume'].apply(lambda x : np.cos(x))
df['V2'] = df['Volume'].apply(lambda x : np.sin(x))
df['V3'] = df['Volume'].apply(lambda x : np.log2(x))
Volume = df['Volume']
df.drop(labels='Volume',axis=1,inplace=True)
df['V4'] = (df['openA']+df['closeA'])/2
df['V5'] = (df['openB']+df['closeB'])/2
df['V6'] = np.sin(Volume)**2
df['V7'] = np.cos(Volume)**2
df['V8'] = np.log2(Volume)**2
df['V9'] = np.log2(Volume)**3
```

In [361]:

```
dataA = df.drop(labels = ['highA','highB'],axis = 1)
dataB = df.drop(labels = ['lowA','lowB'],axis = 1)
targetA = data['High']
targetB = data['Low']

from sklearn.model_selection import train_test_split
trainA = dataA.iloc[0:3000,:]
testA = dataA.iloc[3000:,:]
y_trainA = targetA[0:3000]
y_testA = targetA[3000:]

trainB = dataB.iloc[0:3000,:]
testB = dataB.iloc[3000:,:]
y_trainB = targetB[0:3000]
y_testB = targetB[3000:]
```

**SetA**

In [362]:

```
from sklearn.linear_model import LinearRegression

model = LinearRegression()
model.fit(trainA,y_trainA)
y_testA_pred = model.predict(testA)
print(type(y_testA_pred))
print(len(y_testA))

# MSE
y_testA = list(y_testA)
sum = 0
for i in range(len(y_testA)):
  sum+=(y_testA[i]-y_testA_pred[i])**2
MSE = 1/len(y_testA)*(sum)

print('MSE setA:',MSE)
```

```
<class 'numpy.ndarray'>
1406
MSE setA: 75.90741921065161
```

**setB**

In [363]:

```
from sklearn.linear_model import LinearRegression
```

```python
from sklearn.metrics import accuracy_score
model = LinearRegression()
model.fit(trainB,y_trainB)
y_testB_pred = model.predict(testB)
print(type(y_testB_pred))
print(len(y_testB))

# MSE
y_testB = list(y_testB)
sum = 0
for i in range(len(y_testB)):
  sum+=(y_testB[i]-y_testB_pred[i])**2
MSE = 1/len(y_testB)*(sum)

print('MSE setB :',MSE)
```

```
<class 'numpy.ndarray'>
1406
MSE setB : 77.22276882028312
```

In [364]:

```python
df
```

Out[364]:

| | MM | DD | YYYY | openA | openB | highA | highB | lowA | lowB | closeA | ... | Day | V1 | V2 | V3 | V4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 8 | 19 | 2004 | 50.0 | 0.05 | 52.0 | 0.08 | 48.0 | 0.03 | 50.0 | ... | 0 | 0.739274 | -0.673405 | 25.412451 | 50.0 |
| **1** | 8 | 20 | 2004 | 51.0 | 0.56 | 55.0 | 0.59 | 50.0 | 0.30 | 54.0 | ... | 1 | -0.928135 | -0.372244 | 24.444702 | 52.5 |
| **2** | 8 | 23 | 2004 | 55.0 | 0.43 | 57.0 | 0.80 | 55.0 | 0.58 | 55.0 | ... | 2 | -0.341052 | -0.940045 | 24.121877 | 55.0 |
| **3** | 8 | 24 | 2004 | 56.0 | 0.68 | 56.0 | 0.86 | 52.0 | 0.84 | 52.0 | ... | 3 | 0.946008 | 0.324143 | 23.862054 | 54.0 |
| **4** | 8 | 25 | 2004 | 53.0 | 0.53 | 54.0 | 0.05 | 52.0 | 0.99 | 53.0 | ... | 4 | -0.900512 | 0.434831 | 23.131414 | 53.0 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **4401** | 2 | 10 | 2022 | 2794.0 | 0.07 | 2830.0 | 0.69 | 2759.0 | 0.14 | 2772.0 | ... | 5 | 0.335246 | 0.942130 | 20.907199 | 2783.0 |
| **4402** | 2 | 11 | 2022 | 2772.0 | 0.00 | 2783.0 | 0.13 | 2668.0 | 0.00 | 2686.0 | ... | 6 | 0.233530 | -0.972350 | 20.927379 | 2729.0 |
| **4403** | 2 | 14 | 2022 | 2665.0 | 0.13 | 2726.0 | 0.00 | 2665.0 | 0.13 | 2711.0 | ... | 0 | -0.551828 | -0.833958 | 20.708852 | 2688.0 |
| **4404** | 2 | 15 | 2022 | 2751.0 | 0.41 | 2762.0 | 0.17 | 2716.0 | 0.43 | 2732.0 | ... | 1 | -0.344144 | -0.938917 | 20.347327 | 2741.5 |
| **4405** | 2 | 16 | 2022 | 2733.0 | 0.93 | 2741.0 | 0.61 | 2700.0 | 0.00 | 2721.0 | ... | 2 | -0.115133 | -0.993350 | 19.361021 | 2727.0 |

**4406 rows × 24 columns**

**Observations**

1. **The Model is Time Series Data**
2. **Data is falling on a straight line , Thats why picking LinearRegression is the best choice**
3. **Initially setA and setB are having MSE values 84 and 76 respectively**
4. **After adding new features and doing feature Transformation MSE of set a improved to 76 and set B 77.**
5. **Extra 17 features are added to improve model performance**
6. **MSE can further be improved by adding some more features and doing feature selection.**