In [1]:

```python
import pandas as pd
import numpy as np
import datetime
import seaborn as sns

import matplotlib.pyplot as plt
import matplotlib.mlab as mlab
import matplotlib
plt.style.use('ggplot')
from matplotlib.pyplot import figure

%matplotlib inline
matplotlib.rcParams['figure.figsize'] = (12,8)

pd.options.mode.chained_assignment = None

from collections import Counter
```

In [2]:

```python
# read the data
df = pd.read_csv('all_stocks_5yr.csv')

# shape and data types of the data
print("Shape of our data is: ", df.shape)
print()

# type of each data
print("Data type is: ")

dType = pd.DataFrame(df.dtypes, columns = ['Type'])

dType
```

```
Shape of our data is:  (619040, 7)

Data type is:
```

Out[2]:

	Type
date	object
open	float64
high	float64
low	float64
close	float64
volume	int64
Name	object

In [3]:
```
df
```
Out[3]:

	date	open	high	low	close	volume	Name
0	2013-02-08	15.07	15.12	14.63	14.75	8407500	AAL
1	2013-02-11	14.89	15.01	14.26	14.46	8882000	AAL
2	2013-02-12	14.45	14.51	14.10	14.27	8126000	AAL
3	2013-02-13	14.30	14.94	14.25	14.66	10259500	AAL
4	2013-02-14	14.94	14.96	13.16	13.99	31879900	AAL
...	...	...	...	...	...	...	...
619035	2018-02-01	76.84	78.27	76.69	77.82	2982259	ZTS
619036	2018-02-02	77.53	78.12	76.73	76.78	2595187	ZTS
619037	2018-02-05	76.64	76.92	73.18	73.83	2962031	ZTS
619038	2018-02-06	72.74	74.56	72.13	73.27	4924323	ZTS
619039	2018-02-07	72.70	75.00	72.69	73.86	4534912	ZTS

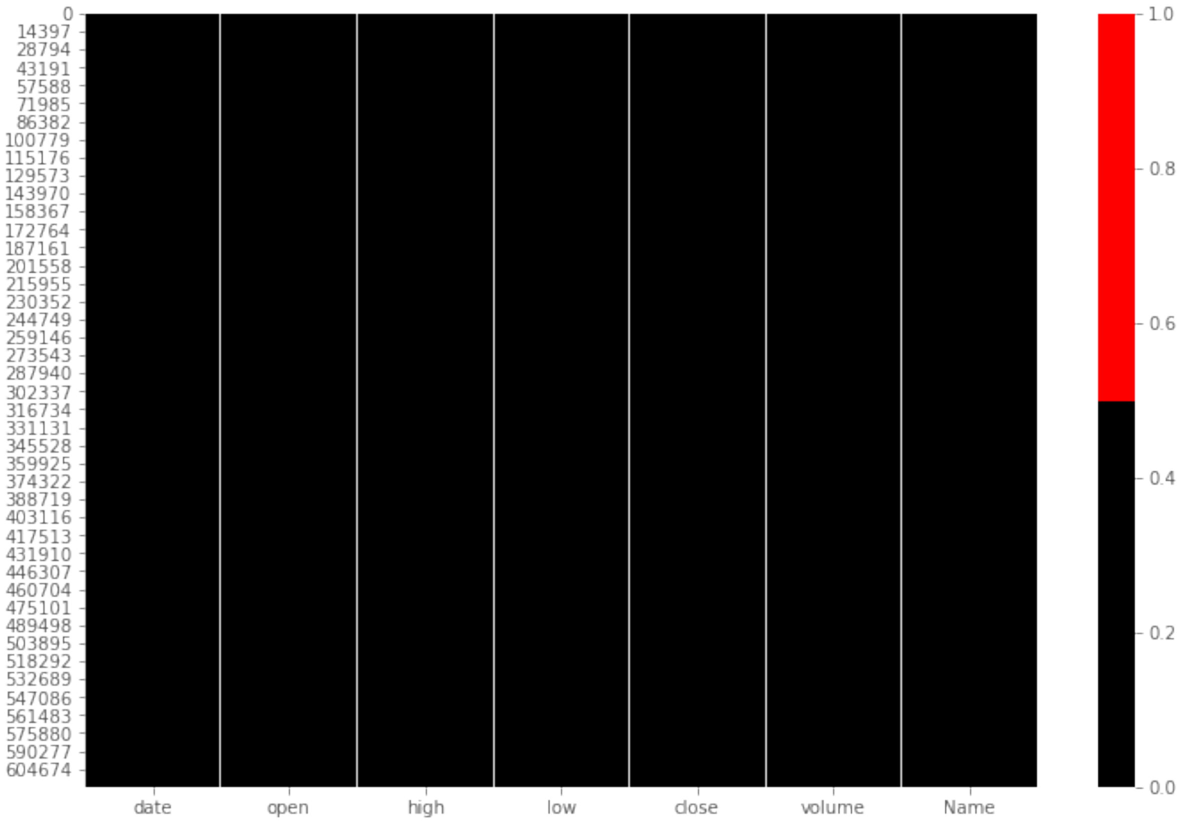
619040 rows × 7 columns

In [4]:
```
# 1. Clean the data
```
In [5]:
```
# ** Missing data **
```
In [6]:
```
# Display Column with missing value
print("Number of missing data per column: ")
df.isnull().sum()
```
```
Number of missing data per column:
```
Out[6]:
```
date       0
open      11
high       8
low        8
close      0
volume     0
Name       0
dtype: int64
```

In [7]:

```
# Visualization: number of missing value is in red, black is no
sns.heatmap(df[df.columns[0:7]].isnull(), cmap=sns.color_palett

# Notice that open has 11 missing value and high and low all ha
# value that we can't see it in the visualization below
```

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb973b8cac0>



In [8]:

```
# To handle with missing data, we decide to impute the missing
# of the same feature that's not missing. There are 619040 diff
# only less than 12 missing values. It's such a small number th
# impute it
df['open'] = df['open'].fillna(df['open'].median())
df['high'] = df['high'].fillna(df['high'].median())
df['low'] = df['low'].fillna(df['low'].median())
```

In [9]:

```
# Display Column with missing value after handling missing valu
print("Number of missing data per column after handling missing
df.isnull().sum()
```

```
Number of missing data per column after handling missing values:
```

Out[9]:

```
date      0
open      0
high      0
low       0
close     0
volume    0
Name      0
dtype: int64
```

In [ ]:

```
1
```

In [10]:

```
# ** Outliers **
```

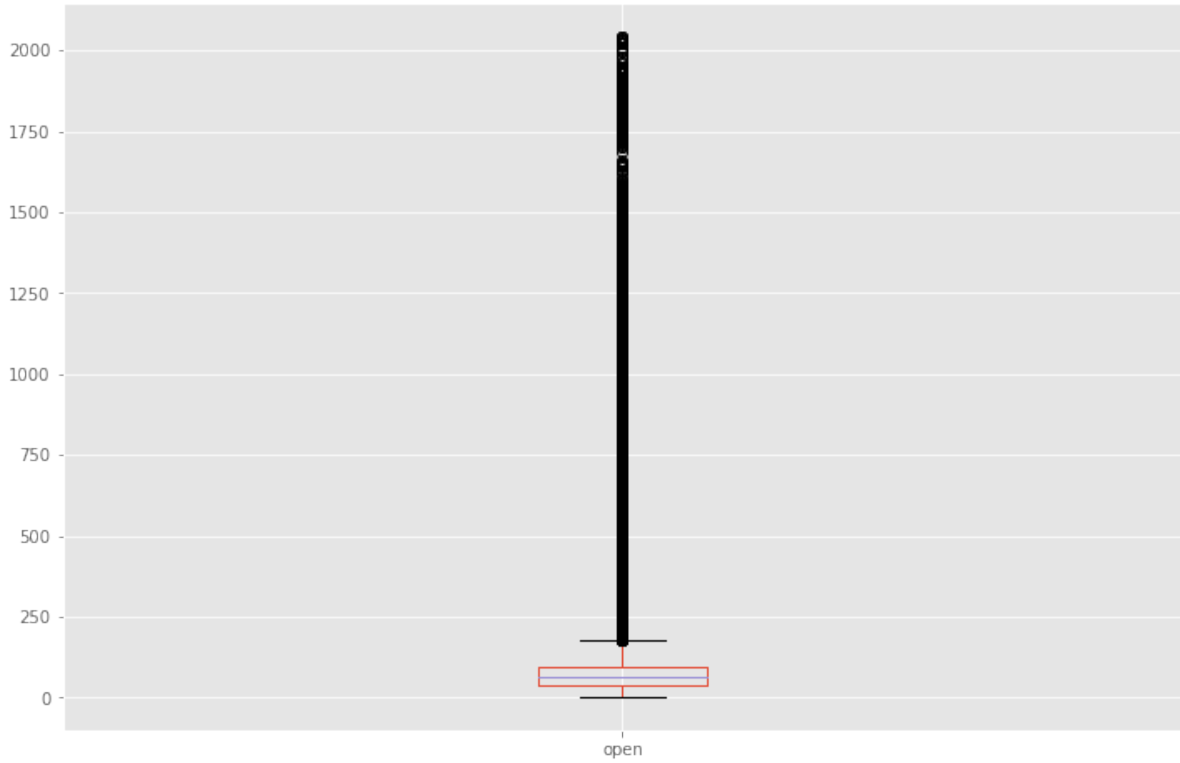
In [11]:

```
# Observing from our data, we can see that there are 5 columns
# open, high, low, close, and volume
```

In [12]:

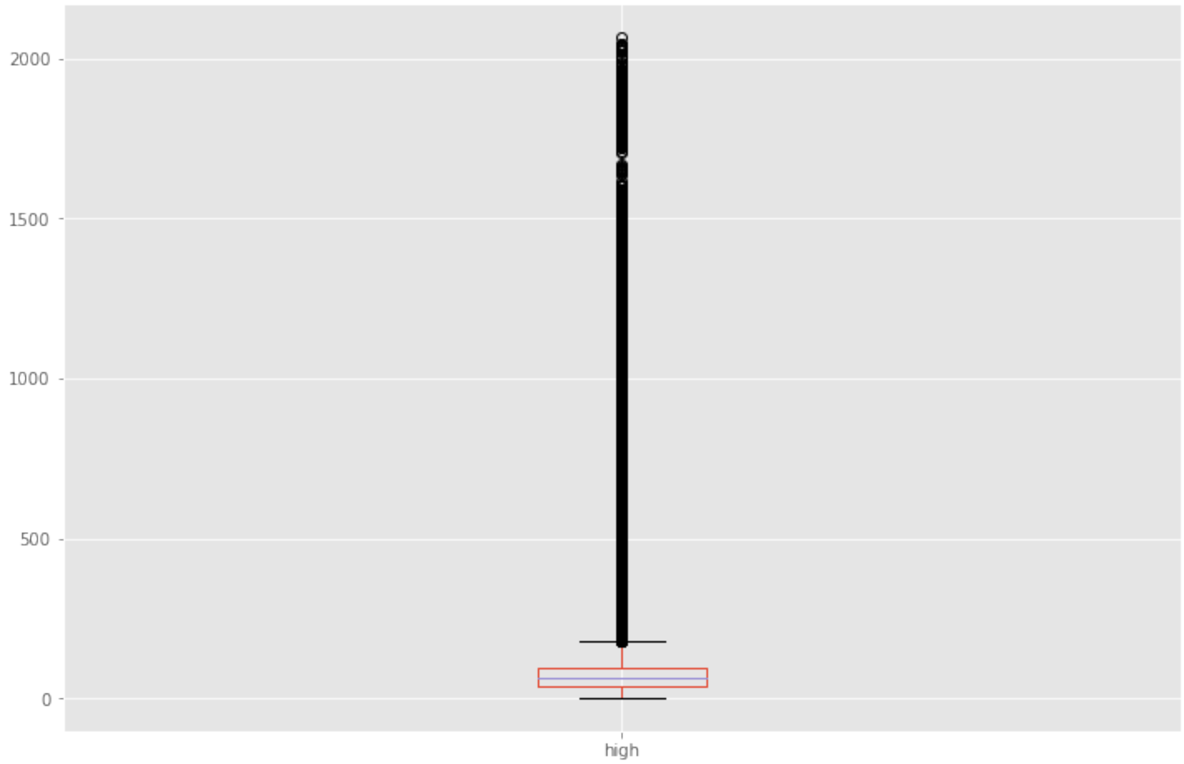
```
# We'll start with open. There seems to be no outliers
df.boxplot(column=['open'])
```

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb959e4e5b0>



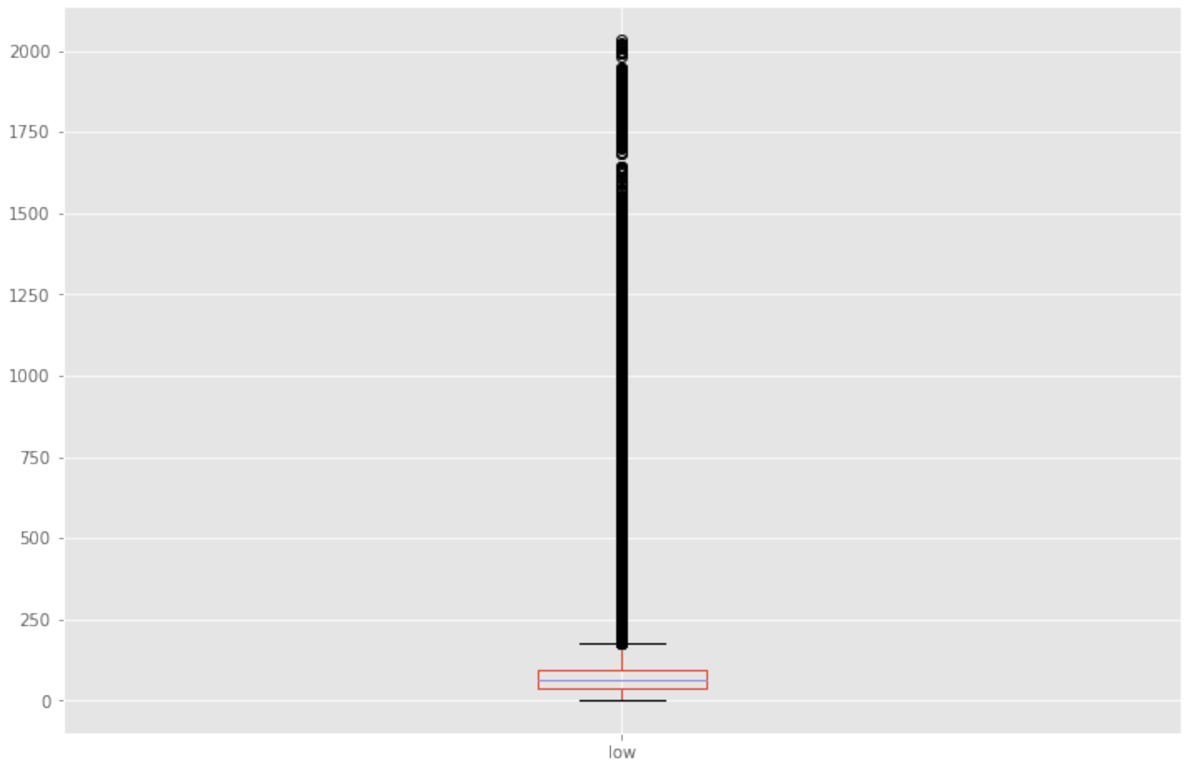
In [13]:
```
# Next is high. There seems to be no outliers
df.boxplot(column=['high'])
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb959fd77c0>



In [14]:
```
# Next is high. There seems to be no outliers
df.boxplot(column=['low'])
```

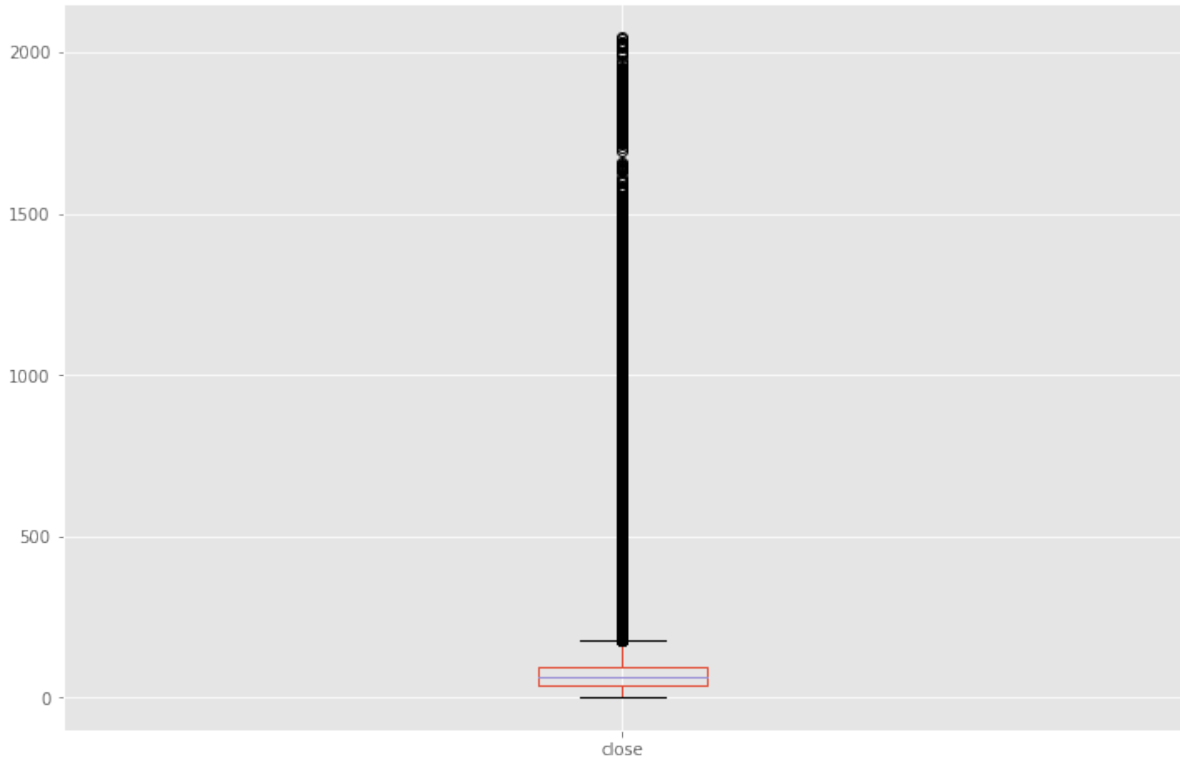
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb95a3b47f0>



In [15]:

```python
# Next is close. There seems to be no outliers
df.boxplot(column=['close'])
```

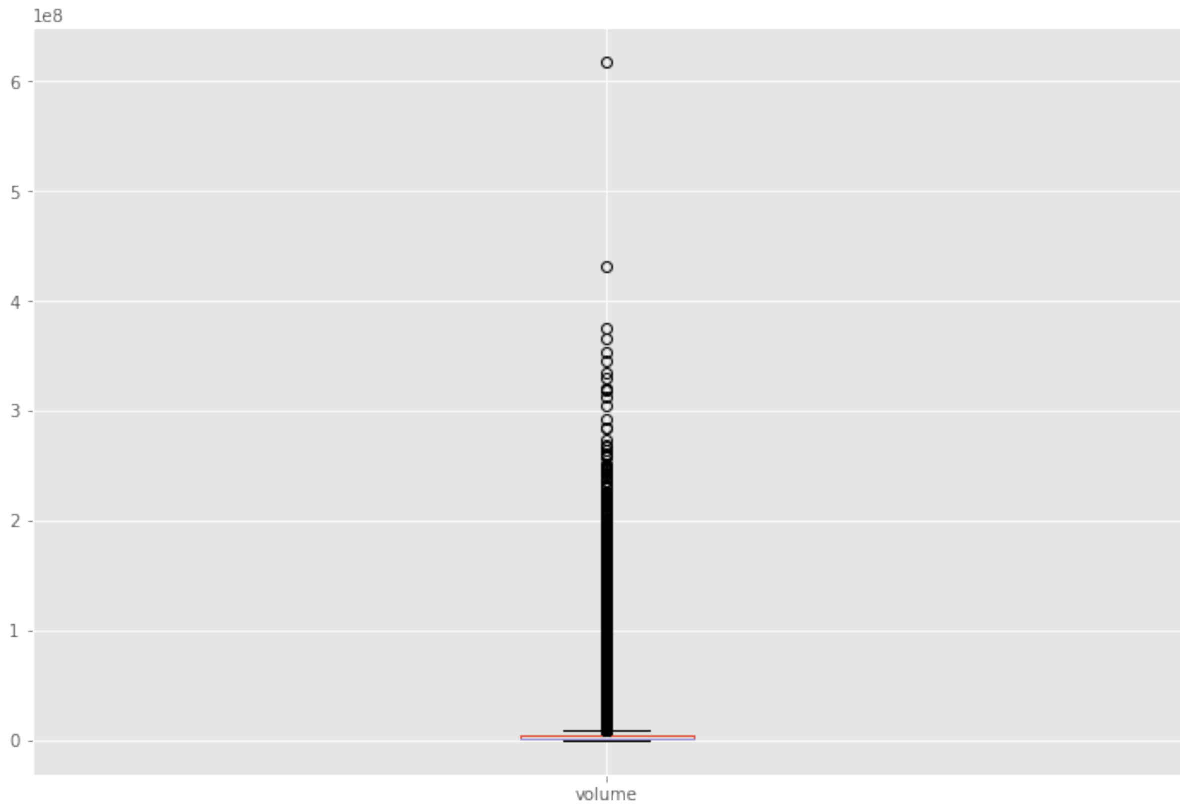
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb95bc54610>



In [16]:

```python
# Next is volumn.
df.boxplot(column=['volume'])
```

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb95c193b20>



In [17]:
```
# Seems like we have an outlier. We can look at the descriptive
df['volume'].describe()
```

Out[17]:
```
count    6.190400e+05
mean     4.321823e+06
std      8.693610e+06
min      0.000000e+00
25%      1.070320e+06
50%      2.082094e+06
75%      4.284509e+06
max      6.182376e+08
Name: volume, dtype: float64
```

In [18]:
```
# As you can see, the maximum of 6.182376e+08 is our outlier be
# However, we decide to keep with outlier because it's an impor
# spike in a certain day, which can indicate good news and bad
```

In [ ]:
```

```

In [19]:
```
# ** Noisy data **
# First, we will check for repetitive data. I want to find colu
for col in df.columns:
    if (df[col].value_counts(dropna=False)/len(df.index)).iloc[
        print('{0}: {1:.5f}%'.format(col, (df[col].value_counts
        print()

# Nothing got printed, which means more than 90% of the data ar
```

In [20]:
```
# Second, we will check for irrelevant value. we have skimmed t
# high and low don't really provide any valuable information fo
# For this project, we only interest in the open and close valu
# the end of the day
df = df.drop(['high', 'low'], axis=1)

# Now we only have 5 columns
print("Shape of our data is: ", df.shape)
print()
```

```
Shape of our data is:  (619040, 5)
```

In [21]:
```
# Third, we will check for duplicated data by checking if there
# date and name together shoule be unique as it's describing a
if df[df.duplicated(subset=['Name','date'])].empty:
    print("There's no duplicated row")
else:
    print("There're duplicated rows")

# Seems like we have no duplicated row
```

```
There's no duplicated row
```

In [ ]:
```

```

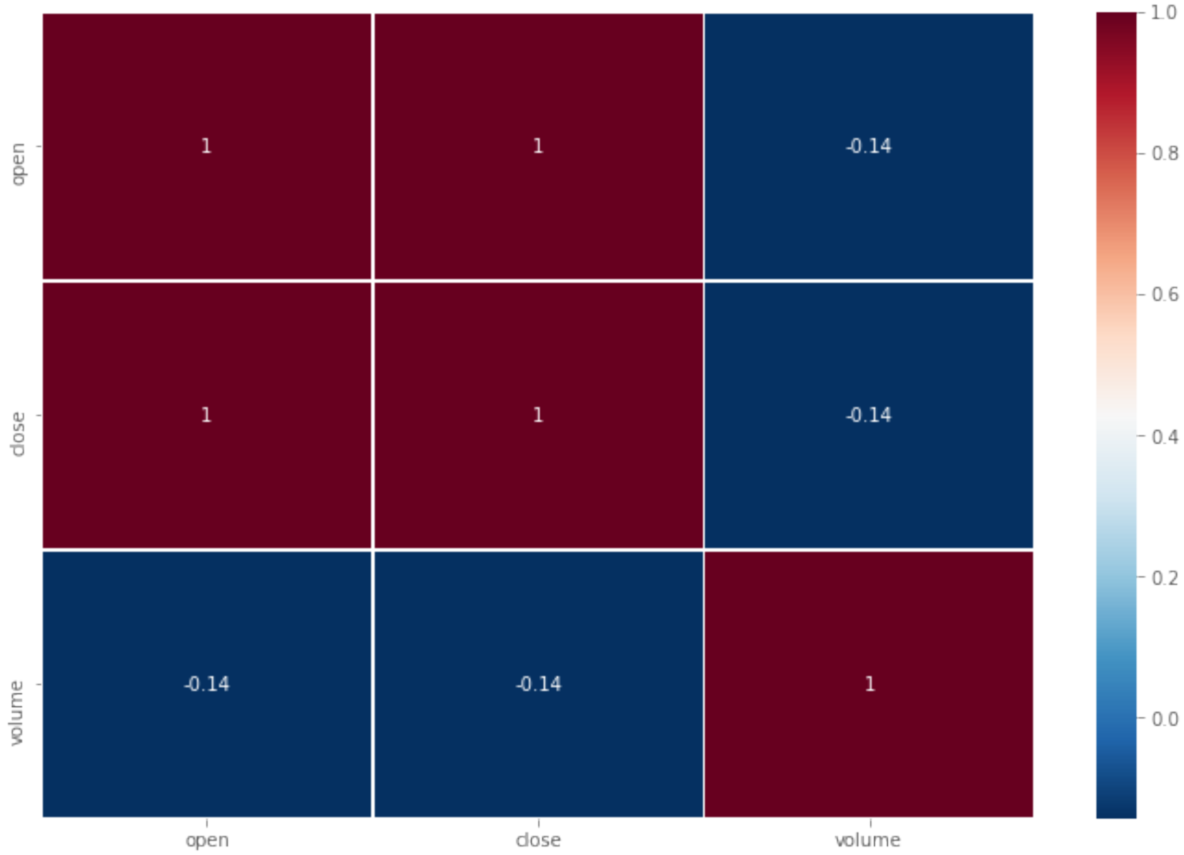
In [22]:
```python
# ** Inconsistent Data **
```

In [23]:
```python
# First, inconsistent usage of upper and lower cases in categor
# put all letters to upper cases
df['Name'] = df['Name'].str.upper()
```

In [24]:
```python
# Second, column date doesn't have the correct data format so I
# object to datetime for easier analysis later
```

In [25]:
```python
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sb

# we check for correlation between the features using the Pears
corr = df.corr(method='pearson')

# print the correlation table
corr

# we print the heatmap of the correaltion table
sb.heatmap(corr,xticklabels=corr.columns, yticklabels=corr.colu
cmap='RdBu_r', annot=True, linewidth=0.5)

# The dark maroon cells represent highly correlated features of
```

Out[25]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb9503a7a60>
```



In [26]:

```python
# We design a function to visualize the independent and depende
def OpenClosePlot(stock, name):
    stock_df=stock[['date','open','close']]

    #Plot Open vs Close
    tickvalues = range(0,20)
    stock_df[['open','close']].tail(20).plot(kind='bar',figsize
    plt.grid(which='major', linestyle='-', linewidth='0.5', col
    plt.grid(which='minor', linestyle=':', linewidth='0.5', col
    plt.xticks(tickvalues, stock.date[len(stock)-20:])
    plt.show()

Stock = input("Stock Name: ").upper()
stock_df = df.loc[df['Name'] == Stock]
OpenClosePlot(stock_df, Stock)
```

```
Stock Name: amgn
```

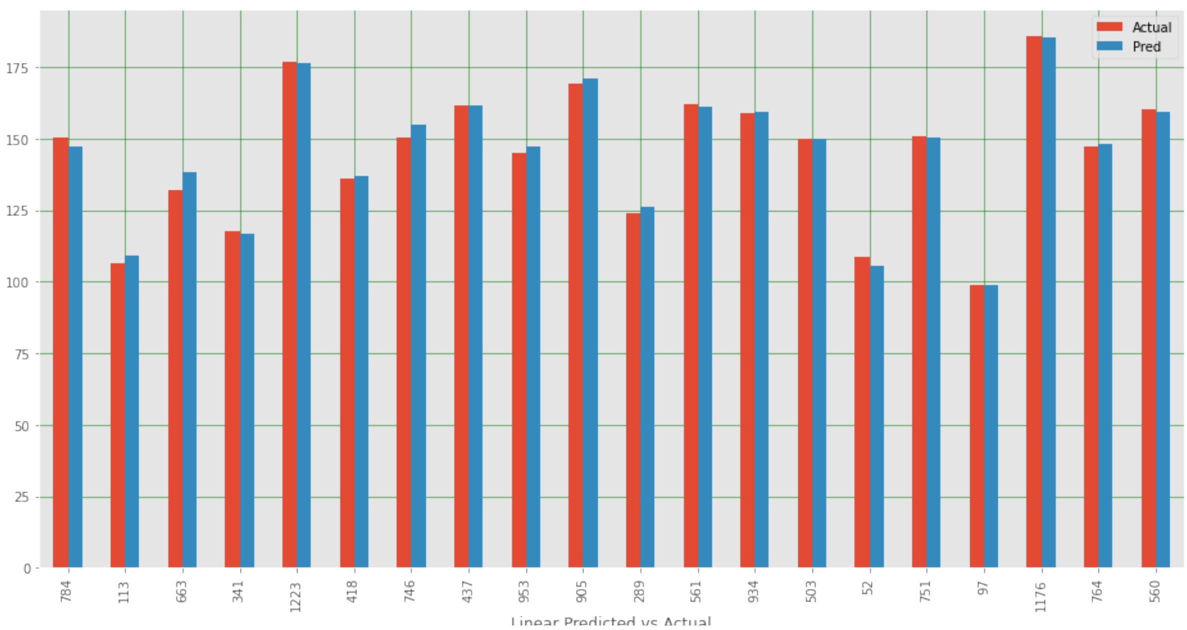
In [27]:

```python
# Model training and testing
stock_df['date'] = pd.to_datetime(stock_df['date'], format='%Y-

stock_df['year']=stock_df['date'].dt.year
stock_df['month']=stock_df['date'].dt.month
stock_df['day']=stock_df['date'].dt.day

stock_df = stock_df[['day', 'month', 'year', 'open', 'close']]
stock_df.head(10)

X = stock_df.iloc[:,stock_df.columns !='close']
Y= stock_df.iloc[:, 4]

Y = Y.reset_index(drop = True)

# X = X.set_index(X['day'] + X['month'] + X['year'])
# X
```

In [28]:

```python
# We train the model after testing and splitting the data
from sklearn.model_selection import train_test_split
from sklearn import model_selection
from sklearn.model_selection import KFold
import sklearn.metrics as sm

x_train,x_test,y_train,y_test= train_test_split(X,Y,test_size=.

# Use linear regression to fit the training data
model=LinearRegression()
model.fit(x_train,y_train)

# predict the values using k-fold
y_pred=model.predict(x_test)
kfold = model_selection.KFold(n_splits=5)
results_kfold = model_selection.cross_val_score(model, x_test,
print("K-Fold Accuracy: ", results_kfold.mean()*100)

print("Score Accuracy: ", model.score(x_test, y_test))

print("Mean absolute error =", round(sm.mean_absolute_error(y_t
print("Mean squared error =", round(sm.mean_squared_error(y_tes
print("Median absolute error =", round(sm.median_absolute_error
print("Explain variance score =", round(sm.explained_variance_s
print("R2 score =", round(sm.r2_score(y_test, y_pred), 2))

plot=pd.DataFrame({'Actual':y_test,'Pred':y_pred})
plot.head(20).plot(kind='bar',figsize=(16,8))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='
plt.xlabel("Linear Predicted vs Actual")
plt.show()
```

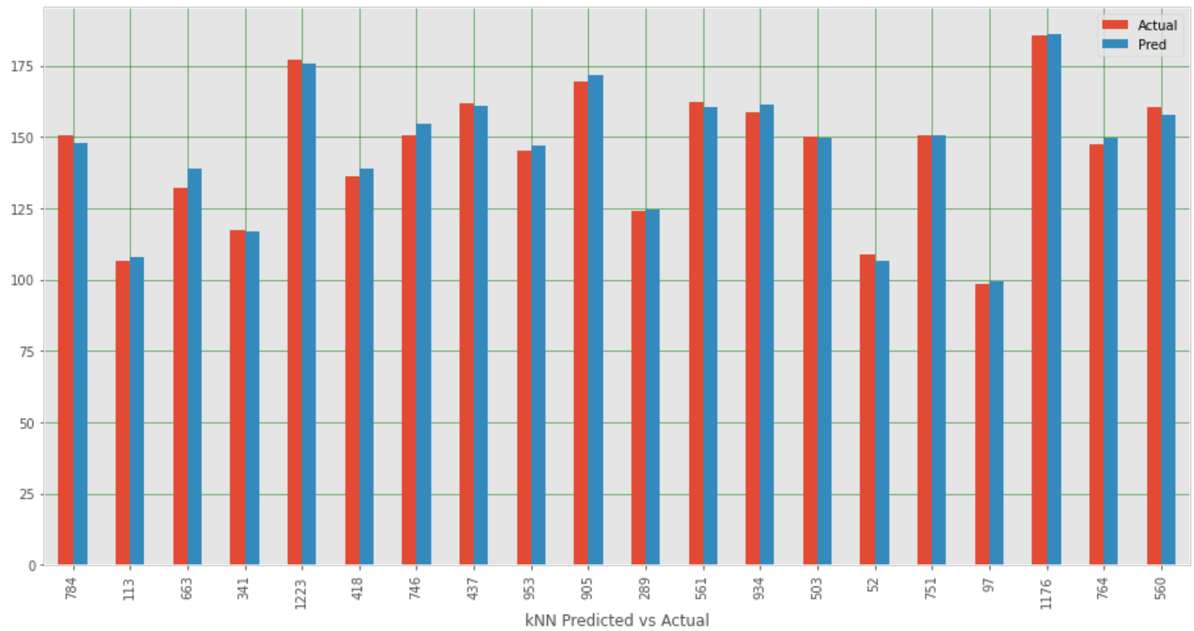
```
K-Fold Accuracy:  99.42777021462138
Score Accuracy:  0.9944887855030116
Mean absolute error = 1.41
Mean squared error = 3.71
Median absolute error = 1.03
Explain variance score = 0.99
R2 score = 0.99
```



In [29]:

```python
# KNN model training
from sklearn.neighbors import KNeighborsRegressor

knn_regressor=KNeighborsRegressor(n_neighbors = 5)
knn_model=knn_regressor.fit(x_train,y_train)
y_knn_pred=knn_model.predict(x_test)

knn_kfold = model_selection.KFold(n_splits=20)
results_kfold = model_selection.cross_val_score(knn_model, x_te
print("K-Fold Accuracy: ", results_kfold.mean()*100)

print("Score Accuracy: ", knn_model.score(x_test, y_test))

print("Mean absolute error =", round(sm.mean_absolute_error(y_t
print("Mean squared error =", round(sm.mean_squared_error(y_tes
print("Median absolute error =", round(sm.median_absolute_error
print("Explain variance score =", round(sm.explained_variance_s
print("R2 score =", round(sm.r2_score(y_test, y_knn_pred), 2))

plot_knn_df=pd.DataFrame({'Actual':y_test,'Pred':y_knn_pred})
plot_knn_df.head(20).plot(kind='bar',figsize=(16,8))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='
plt.xlabel("kNN Predicted vs Actual")
plt.show()
```

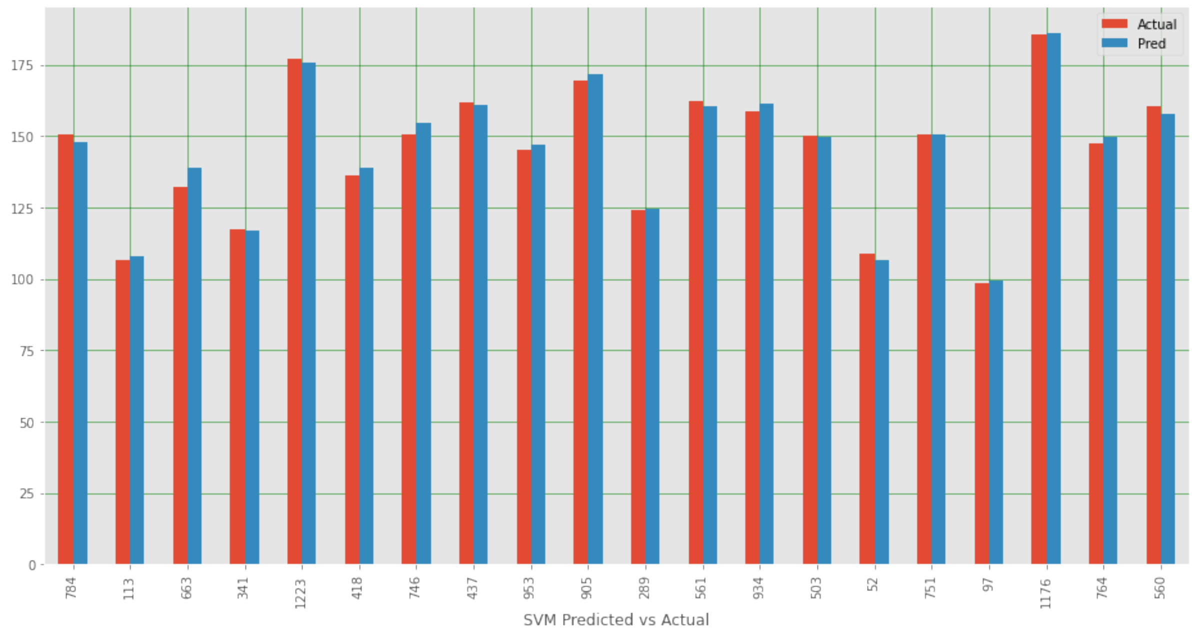
```
K-Fold Accuracy:  98.68568551726746
Score Accuracy:  0.9932669296352159
Mean absolute error = 1.63
Mean squared error = 4.54
Median absolute error = 1.33
Explain variance score = 0.99
R2 score = 0.99
```



In [30]:

```python
from sklearn.svm import SVR
svm_regressor = SVR(kernel='linear')
svm_model=svm_regressor.fit(x_train,y_train)
y_svm_pred=svm_model.predict(x_test)

print("Score Accuracy: ", svm_model.score(x_test, y_test))

print("Mean absolute error =", round(sm.mean_absolute_error(y_t
print("Mean squared error =", round(sm.mean_squared_error(y_tes
print("Median absolute error =", round(sm.median_absolute_error
print("Explain variance score =", round(sm.explained_variance_s
print("R2 score =", round(sm.r2_score(y_test, y_svm_pred), 2))

plot_knn_df=pd.DataFrame({'Actual':y_test,'Pred':y_knn_pred})
plot_knn_df.head(20).plot(kind='bar',figsize=(16,8))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='
plt.xlabel("SVM Predicted vs Actual")
plt.show()
```

```
Score Accuracy:  0.994264659399689
Mean absolute error = 1.44
Mean squared error = 3.86
Median absolute error = 0.97
Explain variance score = 0.99
R2 score = 0.99
```



In [40]:

```python
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.model_selection import train_test_split

# Get the stock data
df = df = pd.read_csv('AMZN.csv')
# Take a look at the data
print(df)

# Get the Adjusted Close Price
df = df[['Adj Close']]
```

```
            Date         Open         High          Low         Clos
e  \
0    2019-12-02  1804.400024  1805.550049  1762.680054  1781.59997
6
1    2019-12-03  1760.000000  1772.869995  1747.229980  1769.95996
1
2    2019-12-04  1774.010010  1789.089966  1760.219971  1760.68994
1
3    2019-12-05  1763.500000  1763.500000  1740.000000  1740.47998
0
4    2019-12-06  1751.199951  1754.400024  1740.130005  1751.59997
6
..          ...          ...          ...          ...          ..
.
248  2020-11-24  3100.500000  3134.250000  3086.260010  3118.06005
9
249  2020-11-25  3141.870117  3198.000000  3140.260010  3185.07006
8
250  2020-11-27  3211.260010  3216.189941  3190.050049  3195.34008
8
251  2020-11-30  3208.479980  3228.389893  3125.550049  3168.04003
9
252  2020-12-01  3188.500000  3248.949951  3157.179932  3220.08007
8

       Adj Close   Volume
0    1781.599976  3925600
1    1769.959961  3380900
2    1760.689941  2670100
3    1740.479980  2823800
4    1751.599976  3117400
..           ...      ...
248  3118.060059  3602100
249  3185.070068  3790400
250  3195.340088  2392900
251  3168.040039  4063900
252  3220.080078  4537000

[253 rows x 7 columns]
```

In [41]:

```python
# A variable for predicting 'n' days out into the future
forecast_out = 20 #'n=10' days
#Create another column (the target ) shifted 'n' units up
df['Prediction'] = df[['Adj Close']].shift(-forecast_out)
```

```
df['Prediction'] = df[['Adj Close']].shift(-forecast_out)
#print the new data set
# print(df.tail())

### Create the independent data set (X)  #######
# Convert the dataframe to a numpy array
X = np.array(df.drop(['Prediction'],1))

#Remove the last '30' rows
X = X[:-forecast_out]
# print(X)

# ### Create the dependent data set (y)  #####
# # Convert the dataframe to a numpy array
y = np.array(df['Prediction'])
# # Get all of the y values except the last '30' rows
y = y[:-forecast_out]
# print(y)

# # Split the data into 80% training and 20% testing
x_train, x_test, y_train, y_test = train_test_split(X, y, test_

# # Create and train the Linear Regression  Model
lr = LinearRegression()
# Train the model
lr.fit(x_train, y_train)

# # Create and train the Support Vector Machine (Regressor)
svr_rbf = SVR(kernel='rbf', C=1e3, gamma=0.1)
svr_rbf.fit(x_train, y_train)

svm_linear = SVR(kernel='linear',)
svm_linear.fit(x_train, y_train)

svm_confidence2 = svm_linear.score(x_test, y_test)
print("linear svm confidence: ", svm_confidence2)

hnn_amazon=KNeighborsRegressor(n_neighbors = 5)
hnn_amazon.fit(x_train,y_train)

print('Knn Confidence', hnn_amazon.score(x_test, y_test))

# # Testing Model: Score returns the coefficient of determinati
# # The best possible score is 1.0
svm_confidence = svr_rbf.score(x_test, y_test)
print("rbf svm confidence: ", svm_confidence)

# # Testing Model: Score returns the coefficient of determinati
# # The best possible score is 1.0
lr_confidence = lr.score(x_test, y_test)
print("lr confidence: ", lr_confidence)
```

```
linear svm confidence:  0.793673175589624
Knn Confidence 0.9110828900264779
rbf svm confidence:  0.5067684817464231
lr confidence:  0.7902567749251435
```

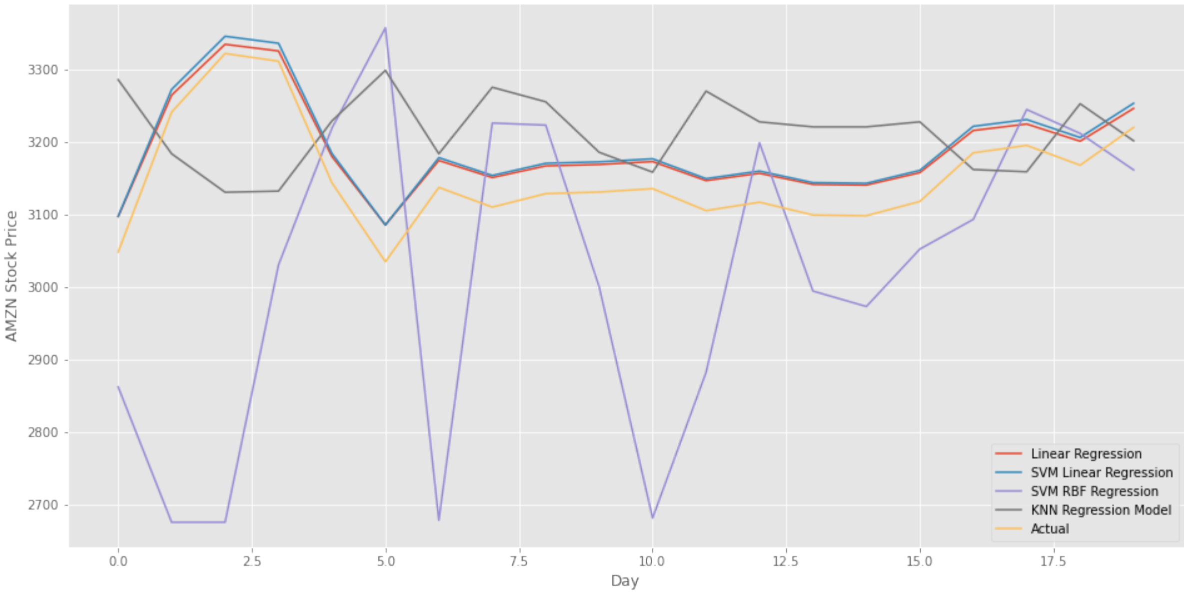
In [42]:

```python
# Set x_forecast equal to the last 30 rows of the original data
x_forecast = np.array(df.drop(['Prediction'],1))[-forecast_out:
print(x_forecast)
```

```
[[3048.409912]
 [3241.159912]
 [3322.      ]
 [3311.370117]
 [3143.73999 ]
 [3035.02002 ]
 [3137.389893]
 [3110.280029]
 [3128.810059]
 [3131.060059]
 [3135.659912]
 [3105.459961]
 [3117.02002 ]
 [3099.399902]
 [3098.389893]
 [3118.060059]
 [3185.070068]
 [3195.340088]
 [3168.040039]
 [3220.080078]]
```

In [43]:

```python
# Print linear regression model predictions for the next '30' d
lr_prediction = lr.predict(x_forecast)
# print(lr_prediction)
# Print support vector regressor model predictions for the next
svm_prediction = svr_rbf.predict(x_forecast)

amazon_knn_pred=hnn_amazon.predict(x_forecast)

svm_linear_predict = svm_linear.predict(x_forecast)

actual = df[len(df) - forecast_out:].reset_index()['Adj Close']
plot = pd.DataFrame({'Linear Regression': lr_prediction, 'SVM L
plot.plot(kind='line', figsize=(16,8))
plt.ylabel("AMZN Stock Price")
plt.xlabel("Day")
plt.show()
```



In [ ]:

```python

```