scraping_yahoofinance

July 29, 2019

0.1 Capstone_project

0.1.1 Project description (Introduction/Business Problem)

A cryptocurrency is a digital or virtual currency that uses cryptography for security. A cryptocurrency is difficult to counterfeit because of this security feature. Many cryptocurrencies are decentralized systems based on blockchain technology, a distributed ledger enforced by a disparate network of computers. A defining feature of a cryptocurrency, and arguably its biggest allure, is its organic nature; it is not issued by any central authority, rendering it theoretically immune to government interference or manipulation.

The first blockchain-based cryptocurrency was Bitcoin, which still remains the most popular and most valuable. Today, there are thousands of alternate cryptocurrencies with various functions or specifications. Some of these are clones of Bitcoin while others are forks, or new cryptocurrencies that split off from an already existing one.

In this project, I will use some financial time series to predict the price of BIT/USD. The model will be used are multiple linear regression and KNN.

0.1.2 Data description

All the data are scraped from yahoo.finance including about 2000 daily records of the following time series: 1. Bitcoin USD (BTC-USD) 2. Treasury Yield 10 Years (^TNX) 3. CBOE Volatility Index (^VIX) 4. S&P 500 (^GSPC) 5. NASDAQ Composite (^IXIC)

Returns will be calculated.

```
In [1]: from bs4 import BeautifulSoup
        import requests
        import pandas as pd
        import numpy as np
        from datetime import datetime
        import time
        from pandas.tseries.offsets import BDay
```

0.1.3 section1

bridge_1() is a function to scrape the 100-period(day/week/month) historical data from yahoo.finance. Only 100 rows of historical data can be scraped every time for yahoo.finance :(But this problem has been solved by the code in section2.

```
In [2]: #start, end, tick, freq

        def bridge_1(start, end, tick, freq):
            url = 'https://finance.yahoo.com/quote/'+tick+'/history?period1='\
                                  +str(start)+'&period2='+str(end)+'&interval='+freq+'&filter=histo

            source = requests.get(url).text

            soup = BeautifulSoup(source, 'lxml')

            table = soup.find('table', class_='W(100%) M(0)') # find the table containing the h

        # Create the column names.
            names = []
            for th in table.thead.find_all('th'):
                names.append(th.text.strip().rstrip().rstrip('*'))

        # Scrape the data and create a DataFrame.
            row = [[]]
            for tr in table.tbody.find_all('tr'):
                try:
                    r=[]
                    for td in tr.find_all('td'):
                        r.append(''.join(td.text.split(','))) #remove the , mark in the values
                    row.append(r) # append each row
                except:
                    pass
            row = row[1:] # slice from 1 row since the 0 row is column names

            df = pd.DataFrame(row, columns=names)
            df['Date'] = pd.to_datetime(df['Date']) # convert str to datetime
            return df
```

0.1.4 section2

Bitcoin USD (BTC-USD)

```
In [3]: # set your parameters :)
        start = '2010 01 01'
        end = '2019 07 24'
        tick = 'BTC-USD'
        freq = '1d'
        days = 2000

        # convert the str to datetime
        start = datetime.strptime(start, '%Y %m %d')
        end = datetime.strptime(end, '%Y %m %d') + BDay(1) # to restore a bug: the latest day
```

```
start = int(time.mktime(start.timetuple())) # convert the datatime to a floating point

for i in range(int(days/100)):
    end = int(time.mktime(end.timetuple()))
    df = bridge_1(start, end, tick, freq)
    if i == 0:
        df2 = df
    if i > 0:
        df2 = df2.append(df, ignore_index=True)
    end = datetime.fromtimestamp(end) - BDay(100) # convert the floating point number

df2 = df2.drop_duplicates() # due to a unknown bug, some days were scraped more than o
df2 = df2[['Date','Open','Close']] # remove the unnecessary columns
df2.replace('-', np.nan, inplace=True)
df2.iloc[:,1:]=df2.iloc[:,1:].astype(float)
df2['Return'] = df2.Close/df2.Open - 1
df2 = df2[['Date','Return']]
print(df2.shape)
df2.head()
```

```
(2000, 2)
```

```
Out[3]:          Date    Return
        0 2019-07-24 -0.008322
        1 2019-07-23 -0.045683
        2 2019-07-22 -0.024638
        3 2019-07-21 -0.016052
        4 2019-07-20  0.021502
```

```
In [4]: bit = df2
```

Treasury Yield 10 Years (^TNX)

```
In [5]: # set your parameters :)
        start = '2010 01 01'
        end = '2019 07 24'
        tick = '%5ETNX'
        freq = '1d'
        days = 2000

        # convert the str to datetime
        start = datetime.strptime(start, '%Y %m %d')
        end = datetime.strptime(end, '%Y %m %d')+BDay(1) # to restore a bug: the latest day is

        start = int(time.mktime(start.timetuple())) # convert the datatime to a floating point

        for i in range(int(days/100)):
            end = int(time.mktime(end.timetuple()))
```

```
        df = bridge_1(start, end, tick, freq)
        if i == 0:
            df2 = df
        if i > 0:
            df2 = df2.append(df, ignore_index=True)
        end = datetime.fromtimestamp(end)-BDay(100) # convert the floating point number to

    df2 = df2.drop_duplicates() # due to a unknown bug, some days were scraped more than o
    df2 = df2[['Date','Open','Close']] # remove the unnecessary columns
    df2.replace('-', np.nan, inplace=True)
    # df2[df2['Open'].str.contains('-') | df2['Close'].str.contains('-')].index[0]
    df2.iloc[:,1:]=df2.iloc[:,1:].astype(float)
    df2['Return'] = df2.Close/df2.Open-1
    df2 = df2[['Date','Return']]
    print(df2.shape)
    df2.head()
```

```
(1932, 2)
```

```
Out[5]:          Date    Return
        0 2019-07-24 -0.000975
        1 2019-07-23  0.012695
        2 2019-07-22 -0.003415
        3 2019-07-19  0.000489
        4 2019-07-18 -0.010199
```

```
In [6]: treasury_yield10 = df2
```

CBOE Volatility Index (^VIX)

```
In [7]: # set your parameters :)
        start = '2010 01 01'
        end = '2019 07 24'
        tick = '%5EVIX'
        freq = '1d'
        days = 2000

        # convert the str to datetime
        start = datetime.strptime(start, '%Y %m %d')
        end = datetime.strptime(end, '%Y %m %d')+BDay(1) # to restore a bug: the latest day is

        start = int(time.mktime(start.timetuple())) # convert the datatime to a floating point

        for i in range(int(days/100)):
            end = int(time.mktime(end.timetuple()))
            df = bridge_1(start, end, tick, freq)
            if i == 0:
                df2 = df
```

```
    if i > 0:
        df2 = df2.append(df, ignore_index=True)
    end = datetime.fromtimestamp(end)-BDay(100) # convert the floating point number to

df2 = df2.drop_duplicates() # due to a unknown bug, some days were scraped more than o
df2 = df2[['Date','Open','Close']] # remove the unnecessary columns
df2.replace('-', np.nan, inplace=True)
df2.iloc[:,1:]=df2.iloc[:,1:].astype(float)
df2['Return'] = df2.Close/df2.Open-1
df2 = df2[['Date','Return']]
print(df2.shape)
df2.head()
```

```
(1932, 2)
```

Out[7]:

	Date	Return
0	2019-07-24	-0.057031
1	2019-07-23	-0.060358
2	2019-07-22	-0.070103
3	2019-07-19	0.085650
4	2019-07-18	-0.063668

In [8]:
```
vix = df2
```

S&P 500 (^GSPC)

In [9]:
```
# set your parameters :)
start = '2010 01 01'
end = '2019 07 24'
tick = '%5EGSPC'
freq = '1d'
days = 2000

# convert the str to datetime
start = datetime.strptime(start, '%Y %m %d')
end = datetime.strptime(end, '%Y %m %d')+BDay(1) # to restore a bug: the latest day is

start = int(time.mktime(start.timetuple())) # convert the datatime to a floating point

for i in range(int(days/100)):
    end = int(time.mktime(end.timetuple()))
    df = bridge_1(start, end, tick, freq)
    if i == 0:
        df2 = df
    if i > 0:
        df2 = df2.append(df, ignore_index=True)
    end = datetime.fromtimestamp(end)-BDay(100) # convert the floating point number to
```

```
df2 = df2.drop_duplicates() # due to a unknown bug, some days were scraped more than o
df2 = df2[['Date','Open','Close']] # remove the unnecessary columns
df2.replace('-', np.nan, inplace=True)
df2.iloc[:,1:]=df2.iloc[:,1:].astype(float)
df2['Return'] = df2.Close/df2.Open-1
df2 = df2[['Date','Return']]
print(df2.shape)
df2.head()
```

```
(1932, 2)
```

```
Out[9]:         Date    Return
        0 2019-07-24  0.006933
        1 2019-07-23  0.003583
        2 2019-07-22  0.001040
        3 2019-07-19 -0.009204
        4 2019-07-18  0.005452
```

```
In [10]: sp500 = df2
```

NASDAQ Composite (^IXIC)

```
In [11]: # set your parameters :)
         start = '2010 01 01'
         end = '2019 07 24'
         tick = '%5EIXIC'
         freq = '1d'
         days = 2000

         # convert the str to datetime
         start = datetime.strptime(start, '%Y %m %d')
         end = datetime.strptime(end, '%Y %m %d')+BDay(1) # to restore a bug: the latest day i

         start = int(time.mktime(start.timetuple())) # convert the datatime to a floating poin

         for i in range(int(days/100)):
             end = int(time.mktime(end.timetuple()))
             df = bridge_1(start, end, tick, freq)
             if i == 0:
                 df2 = df
             if i > 0:
                 df2 = df2.append(df, ignore_index=True)
             end = datetime.fromtimestamp(end)-BDay(100) # convert the floating point number t

         df2 = df2.drop_duplicates() # due to a unknown bug, some days were scraped more than
         df2 = df2[['Date','Open','Close']] # remove the unnecessary columns
         df2.replace('-', np.nan, inplace=True)
         df2.iloc[:,1:]=df2.iloc[:,1:].astype(float)
```

```
df2['Return'] = df2.Close/df2.Open-1
df2 = df2[['Date','Return']]
print(df2.shape)
df2.head()
```

(1932, 2)

Out[11]:

	Date	Return
0	2019-07-24	0.011442
1	2019-07-23	0.001080
2	2019-07-22	0.003934
3	2019-07-19	-0.011509
4	2019-07-18	0.006806

In [12]:
```
nasdaq = df2
```

Merge all the series into one set

In [13]:
```
df3 = bit.merge(treasury_yield10, on='Date').merge(vix, on='Date')\
    .merge(sp500, on='Date').merge(nasdaq, on='Date')
```

In [14]:
```
df3.columns = ['Date','BIT/USD','T_yield10','VIX','SP500','Nasdaq']
```

In [15]:
```
from scipy import stats
from sklearn import preprocessing

df3.dropna(inplace=True) #drop the missing values
print(df3.shape)

df4 = preprocessing.StandardScaler().fit(df3.iloc[:,1:]).transform(df3.iloc[:,1:]) #n
df4 = pd.DataFrame(df4)
print(df4.shape)

df4 = pd.concat([df3[['Date']],df4], axis=1, join='inner', ignore_index=True)
print(df4.shape)

df4.columns = ['Date','BIT/USD','T_yield10','VIX','SP500','Nasdaq']
df4.head()
```

(1389, 6)
(1389, 5)
(1388, 6)

Out[15]:

	Date	BIT/USD	T_yield10	VIX	SP500	Nasdaq
0	2019-07-24	-0.133735	-0.047081	-0.812711	0.916496	1.409543
1	2019-07-23	-0.490299	0.833123	-0.863676	0.461426	0.101935
2	2019-07-22	-0.289452	-0.204191	-1.012988	0.115922	0.462121
3	2019-07-19	-0.148872	0.047132	1.373350	-1.275574	-1.486597
4	2019-07-18	0.873084	-0.641041	-0.914392	0.715293	0.824492

In [16]:
```
df4.boxplot()
```

Out[16]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x118045860>
```

In [17]:
```
# remove the outliers
df4 = df4[ (df4['T_yield10']<3) & (df4['VIX']<3) & (df4['SP500']<3) & (df4['Nasdaq']<3
print(df4.shape)
```

```
(1341, 6)
```

In [18]:
```
df4.boxplot()
```

Out[18]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x118045860>
```

In [19]:
```
X = df4[['T_yield10','VIX','SP500','Nasdaq']]
print(X.shape)
X.head()
```

```
(1341, 4)
```

Out[19]:

	T_yield10	VIX	SP500	Nasdaq
0	-0.047081	-0.812711	0.916496	1.409543
1	0.833123	-0.863676	0.461426	0.101935
2	-0.204191	-1.012988	0.115922	0.462121
3	0.047132	1.373350	-1.275574	-1.486597
4	-0.641041	-0.914392	0.715293	0.824492

In [20]:
```
y = df4[['BIT/USD']]
print(y.shape)
y.head()
```

```
(1341, 1)
```

Out[20]:

	BIT/USD
0	-0.133735
1	-0.490299
2	-0.289452
3	-0.148872
4	0.873084

0.1.5 section3

In [21]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [22]: df4.corr()

Out[22]:

	BIT/USD	T_yield10	VIX	SP500	Nasdaq
BIT/USD	1.000000	0.012101	0.011591	-0.055449	-0.011020
T_yield10	0.012101	1.000000	-0.135195	0.245889	0.196545
VIX	0.011591	-0.135195	1.000000	-0.618184	-0.681143
SP500	-0.055449	0.245889	-0.618184	1.000000	0.788400
Nasdaq	-0.011020	0.196545	-0.681143	0.788400	1.000000

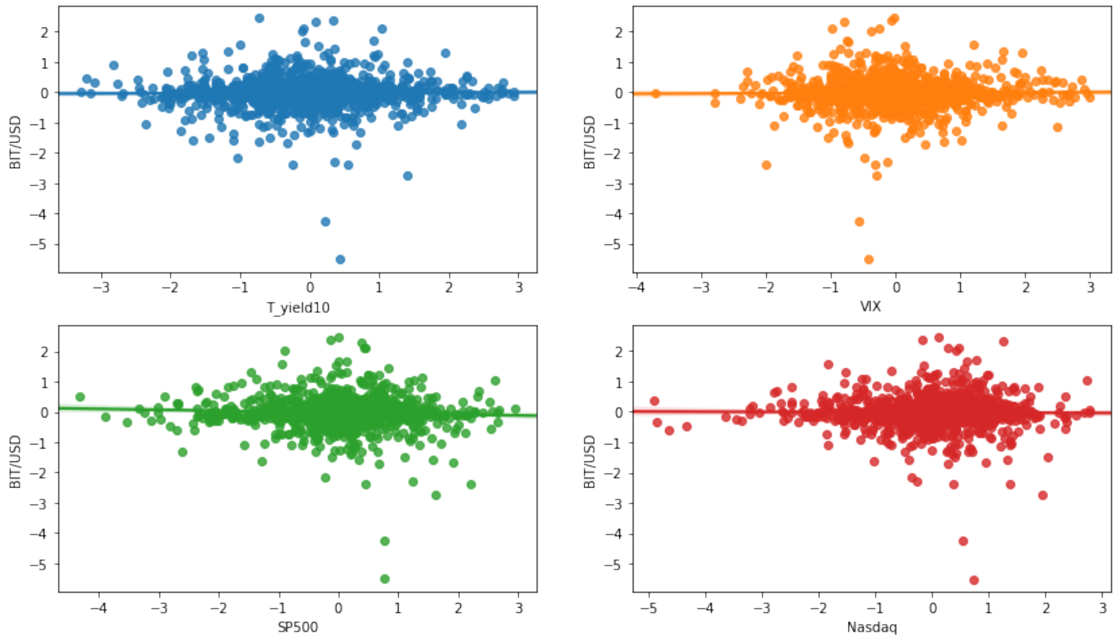
As can be seen from the correlation matrix, there is no strong correlation between the BIT/USE and the others.

In [23]:

```
fig = plt.figure(figsize=(14, 8))

ax0 = fig.add_subplot(2,2,1)
ax1 = fig.add_subplot(2,2,2)
ax2 = fig.add_subplot(2,2,3)
ax3 = fig.add_subplot(2,2,4)

sns.regplot(x='T_yield10', y='BIT/USD', data=df4, ax=ax0)
sns.regplot(x='VIX', y='BIT/USD', data=df4, ax=ax1)
sns.regplot(x='SP500', y='BIT/USD', data=df4, ax=ax2)
sns.regplot(x='Nasdaq', y='BIT/USD', data=df4, ax=ax3)
```

```
/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:1633: FutureWarning: Using a non-tu
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x117b37f60>



There correlation observed from the charts.

```
In [24]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=
```

```
In [25]: X_train.head()
```

```
Out[25]:      T_yield10       VIX     SP500    Nasdaq
         510  -0.420617  1.905003 -1.572728 -1.813357
         376  -0.668737 -0.715574  0.392985  0.416110
         10   -1.210209 -1.377287  0.146021  0.263909
         857   0.929201 -0.762883  0.008029  0.794584
         826  -0.832951  0.499571 -0.512631  0.419166
```

Linear Regression model

```
In [26]: lre=LinearRegression()
```

```
In [27]: lre.fit(X_train[['T_yield10']], y_train)
         lre.score(X_test[['T_yield10']], y_test)
```

```
Out[27]: -0.004269677406289363
```

```
In [28]: lre.fit(X_train[['VIX']], y_train)
         lre.score(X_test[['VIX']], y_test)
```

```
Out[28]: -0.0031420271417628154
```

```
In [29]: lre.fit(X_train[['SP500']], y_train)
         lre.score(X_test[['SP500']], y_test)
```

```
Out[29]: -0.005178741417809052
```

```
In [30]: lre.fit(X_train[['Nasdaq']], y_train)
         lre.score(X_test[['Nasdaq']], y_test)
```

```
Out[30]: -0.004899490946022711
```

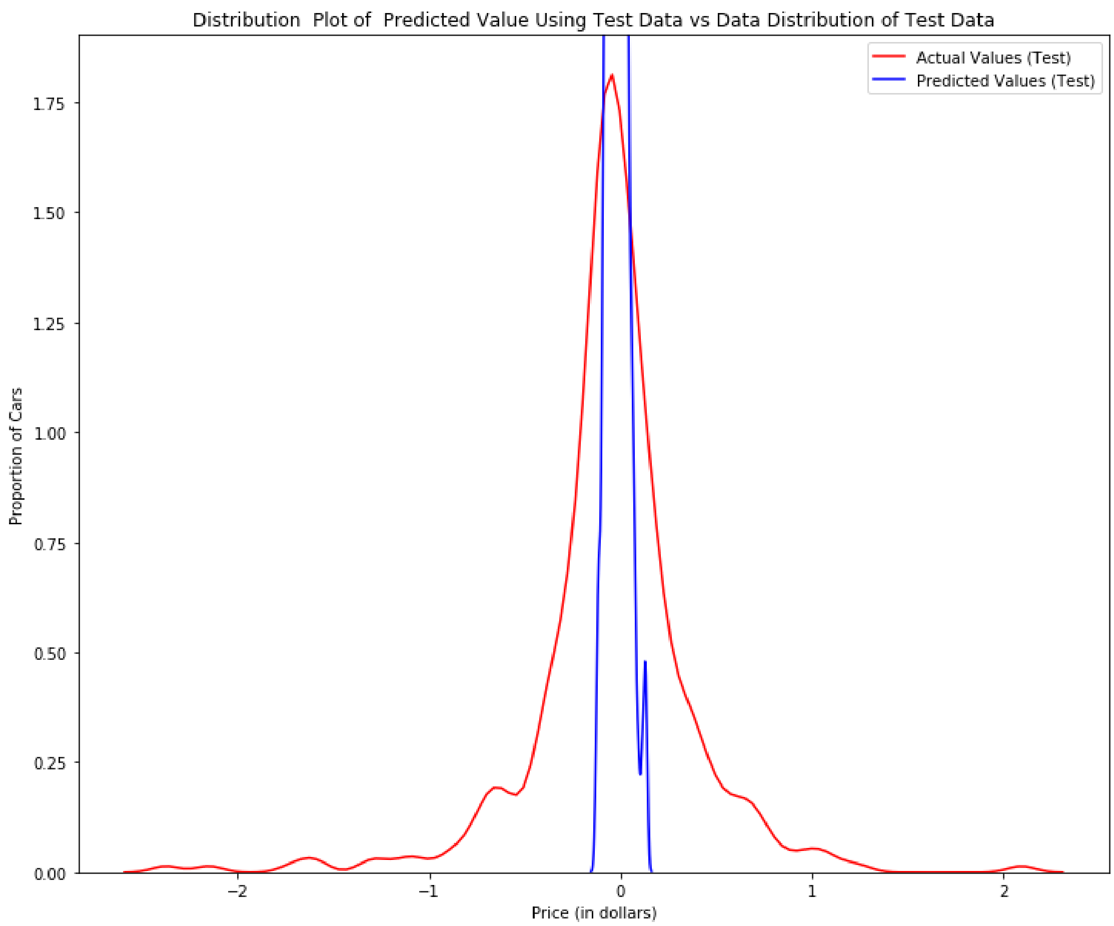
```
In [31]: lre.fit(X_train, y_train)
         yhat_test = lre.predict(X_test)
```

```
In [32]: def DistributionPlot(RedFunction, BlueFunction, RedName, BlueName, Title):
             width = 12
             height = 10
             plt.figure(figsize=(width, height))

             ax1 = sns.distplot(RedFunction, hist=False, color="r", label=RedName)
             ax2 = sns.distplot(BlueFunction, hist=False, color="b", label=BlueName, ax=ax1)
```

```
            plt.title(Title)
            plt.xlabel('Price (in dollars)')
            plt.ylabel('Proportion of Cars')

            plt.show()
            plt.close()
```

```
In [33]: Title='Distribution  Plot of  Predicted Value Using Test Data vs Data Distribution of
         DistributionPlot(y_test,yhat_test,"Actual Values (Test)","Predicted Values (Test)",Ti
```

```
/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:1633: FutureWarning: Using a non-tu
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



0.1.6 Result and conclusion (for MLR)

As can be seen, the multiple linear regression performed pretty badly. There maybe two reason: one is the poor predictability of the features; the onther one is the poor performance of the MLR model.

Further features and models should be considered and searched.

0.1.7 K nearest neighbor (KNN)

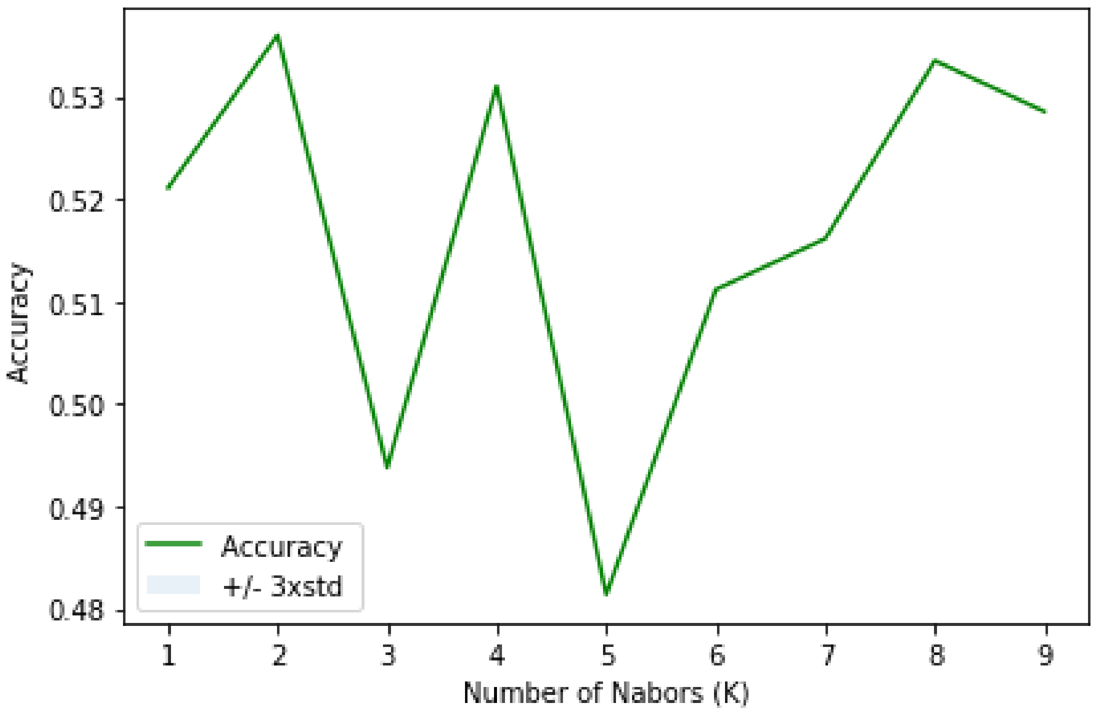
```
In [34]: from sklearn.neighbors import KNeighborsClassifier
         from sklearn import metrics

In [35]: df5 = df4.copy()

In [36]: df5.loc[df5['BIT/USD']>=0,'BIT/USD']=1
         df5.loc[df5['BIT/USD']<0,'BIT/USD']=0

In [37]: df5['BIT/USD'].value_counts()

Out[37]: 0.0    758
         1.0    583
         Name: BIT/USD, dtype: int64

In [38]: X = df5[['T_yield10','VIX','SP500','Nasdaq']]
         y = df5[['BIT/USD']]
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=
```

Calculate the accuracy of KNN for different Ks.

```
In [39]: Ks = 10
         mean_acc = np.zeros((Ks-1))
         std_acc = np.zeros((Ks-1))
         ConfustionMx = [];
         for n in range(1,Ks):

             #Train Model and Predict
             neigh = KNeighborsClassifier(n_neighbors = n).fit(X_train,y_train)
             yhat=neigh.predict(X_test)
             mean_acc[n-1] = metrics.accuracy_score(y_test, yhat)

         mean_acc

/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:8: DataConversionWarning: A column



Out[39]: array([0.52109181, 0.53598015, 0.49379653, 0.53101737, 0.48138958,
                0.51116625, 0.51612903, 0.53349876, 0.52853598])
```

Plot model accuracy for Different number of Neighbors

```
In [40]: plt.plot(range(1,Ks),mean_acc,'g')
         plt.fill_between(range(1,Ks),mean_acc - 1 * std_acc,mean_acc + 1 * std_acc, alpha=0.10
         plt.legend(('Accuracy ', '+/- 3xstd'))
         plt.ylabel('Accuracy ')
         plt.xlabel('Number of Nabors (K)')
         plt.tight_layout()
         plt.show()
```




```
In [41]: print( "The best accuracy was with", mean_acc.max(), "with k=", mean_acc.argmax()+1)
```

```
The best accuracy was with 0.5359801488833746 with k= 2
```

0.1.8 Result

```
In [42]: # write your code here

         k =2
         neigh2 = KNeighborsClassifier(n_neighbors=k).fit(X_train, y_train)
         yhat2 = neigh2.predict(X_test)
         print('Train set accuracy: ', metrics.accuracy_score(y_train, neigh2.predict(X_train))
         print('Test set accuracy: ', metrics.accuracy_score(y_test, yhat2))
```

```
Train set accuracy:  0.7494669509594882
Test set accuracy:  0.5359801488833746
```

```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:4: DataConversionWarning: A colum
  after removing the cwd from sys.path.
```

0.1.9 Conlusion (for KNN)

The 2-KNN model seems not bad from the result. Further exploration should be conducted.

NOTE: to be honest, I am not happy with this work. But my subscription will be due soon...