MDSR Intermediate Report

December 19, 2019

1 Massive Data Storage and Retrieval - Intermediate Report

1.0.1 Project goals and why it is interesting

Recent advances in the field have shown that Reinforcement Learning agents are often capable of learning much more than supervised learning agents within the same problem domain. Moreover, the Bitcoin price history since it's inception shows that it has a very volatile value. ML methods, reinforcement learning (RL) is particularly interesting, especially the Q-learning approach. First, Q-learning does not model the market, instead of focusing on the benefit (Q value) associated with actions. This avoids the errors caused by any market model. Second, Q-learning is suitable to do online learning, which enables quick adaptation to new market status. Third, Q-learning pays attention to long-term benefit rather than instantaneous reward, which is congruent with the goal of stock trading, maximizing long-term profit. Currently, reinforcement learning has been applied in financial analysis and investment by a multitude of researchers.

In this project, we propose to employ Deep Q-learning to build an Algorithmic Cryptocurrency Trading system which can automatically determine what position to hold at each trading time. We apply the deep Q-learning approach where our goal is to build a deep Q-trading system that determines when to buy and sell, based on the current and historical market data.

1.0.2 Source of Data

The historical bitcoin data is taken from the site 'https://www.investing.com/crypto/bitcoin/historical-data'. It has 5 years (1st Jan 2014 - 31st Dec 2018) of bitcoin data

1.0.3 Data Preprocessing & Cleaning

[105]:
```
import matplotlib.pyplot as plt
import os
import pandas as pd
import plotly.graph_objects as go
import pyspark
import urllib.request as urllib2

from pyspark.sql.session import SparkSession
from io import StringIO
%matplotlib inline
```

[106]:
```
url = "http://www.sharecsv.com/dl/90e8a350aaebc4e180d5d2a6c7777214/bitcoin_data.
 ↪csv"
response = urllib2.urlopen(url)
data = response.read()
text = data.decode('utf-8')
data = spark.read.csv(sc.parallelize(text.splitlines()), header=True)
data = data.toPandas()
```

[107]:
```
# Removing the rows with NAN values in the data
data.dropna() #Removing rows with nan values
```

[107]:
```
              Date     Price     Open     High      Low     Vol. Change %
0     Dec 31, 2018   3,709.4  3,815.1  3,819.6  3,658.8  545.83K   -2.77%
1     Dec 30, 2018   3,815.0  3,708.2  3,837.7  3,682.5  519.17K    2.92%
2     Dec 29, 2018   3,706.8  3,861.6  3,899.6  3,696.0  505.41K   -4.01%
3     Dec 28, 2018   3,861.6  3,587.1  3,900.3  3,565.5  565.24K    7.66%
4     Dec 27, 2018   3,586.9  3,793.4  3,822.6  3,560.8  543.44K   -5.45%
...            ...       ...      ...      ...      ...      ...      ...
1821  Jan 05, 2014   1,014.7    924.7  1,029.9    911.4   21.37K    9.74%
1822  Jan 04, 2014     924.7    884.3    932.2    848.3   14.24K    4.57%
1823  Jan 03, 2014     884.3    856.9    888.2    839.4    9.71K    3.19%
1824  Jan 02, 2014     856.9    815.9    886.2    810.5   12.81K    5.02%
1825  Jan 01, 2014     815.9    805.9    829.9    771.0   10.76K    1.24%

[1826 rows x 7 columns]
```

Size of the data

[108]:
```
data.shape
```

[108]:
```
(1826, 7)
```

The above data set has 7 columns and 1826 rows.

Removing Duplicate Rows The next data processing step would be to check if there are any duplicate rows in the date column

[109]:
```
duplicateRows = data[data.duplicated(['Date'])]
print (duplicateRows)
```

```
Empty DataFrame
Columns: [Date, Price, Open, High, Low, Vol., Change %]
Index: []
```

This shows that the date column in the data does not have any duplicate values

Level of the Dataframe Since there are no duplicates in the 'Date' column of the data. The data is in the level of 'Date' column. The 'Date' column can be used as the primary key

Data types of each column

[110]:
```
data.dtypes
```

[110]:
```
Date          object
Price         object
Open          object
High          object
Low           object
Vol.          object
Change %      object
dtype: object
```

In the data, the columns of 'Price','Open', 'High' and 'Low' are of the object type and numeric. This is because these columns use comma for separation of thousands. Hence we need to replace ',' with ''(Null) character and then convert it to numeric data type

[111]:
```
data['Price'] = data['Price'].str.replace(',', '').astype(float)
data['Open'] = data['Open'].str.replace(',', '').astype(float)
data['High'] = data['High'].str.replace(',', '').astype(float)
data['Low'] = data['Low'].str.replace(',', '').astype(float)
```

[112]:
```
data['Date'] = data['Date'].astype('datetime64[ns]')
```

[113]:
```
data['Change %'] = data['Change %'].str.replace('%', '').astype(float)
```

The 'Vol.' column in the data uses 'K' to denote thousands and 'M' to denote Millions. We will have to convert them to float data types. This can be done by identifying the rows with characters 'K' or 'M'. We replace the characters with Null character and convert the column to float. Now one again we determine the rows with characters 'K' and 'M' and replece it with 10**3** and 10**6** respectively, where ** denotes raising the value to its power. Finally this rows with 'K' are multiplied by 10^3, rows with 'M' are multiplied by 10^6 and rows with 'K' and 'M' are multiplied by 1

[114]:
```
data['Vol.'] = (data['Vol.'].replace(r'[KM]+$', '', regex=True).astype(float) *␣
↪data['Vol.'].str.extract(r'[\d\.]+([KM]+)', expand=False).fillna(1).
↪replace(['K','M'], [10**3, 10**6]).astype(int))
```

[115]:
```
data.dtypes
```

[115]:
```
Date          datetime64[ns]
Price                float64
Open                 float64
High                 float64
Low                  float64
Vol.                 float64
Change %             float64
dtype: object
```

[116]:
```
data.head()
```

[116]:

	Date	Price	Open	High	Low	Vol.	Change %
0	2018-12-31	3709.4	3815.1	3819.6	3658.8	545830.0	-2.77
1	2018-12-30	3815.0	3708.2	3837.7	3682.5	519170.0	2.92
2	2018-12-29	3706.8	3861.6	3899.6	3696.0	505410.0	-4.01

```
3 2018-12-28  3861.6  3587.1  3900.3  3565.5  565240.0      7.66
4 2018-12-27  3586.9  3793.4  3822.6  3560.8  543440.0     -5.45
```

[117]:
```
data['Price'].idxmax()
```

[117]:
```
380
```

[118]:
```
data.iloc[94]
```

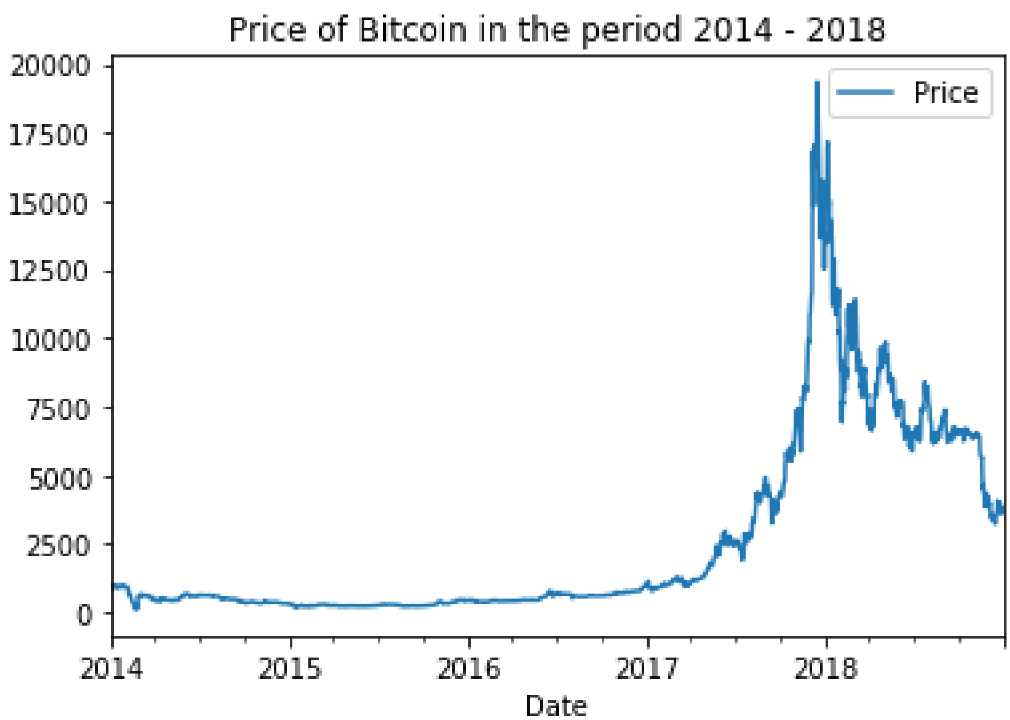
[118]:
```
Date        2018-09-28 00:00:00
Price                      6636
Open                     6685.7
High                     6809.2
Low                      6538.6
Vol.                   9.57e+06
Change %                  -0.79
Name: 94, dtype: object
```

[119]:
```
data['Vol.'].idxmax()
```

[119]:
```
94
```

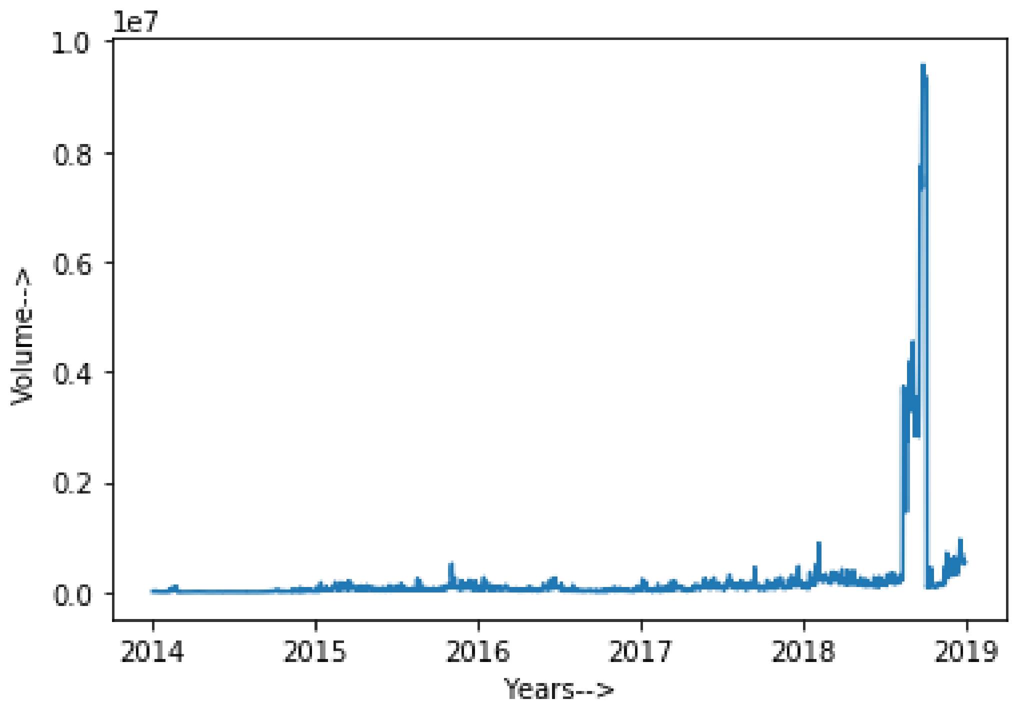
[120]:
```
data.plot(x='Date', y=['Price'], kind='line', title='Price of Bitcoin in the␣
 ↪period 2014 - 2018')
```

[120]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11d6c87f0>
```



[121]:
```
plt.plot(data['Date'],data['Vol.'])
plt.xlabel('Years-->')
plt.ylabel('Volume-->')
```

[121]:
```
Text(0, 0.5, 'Volume-->')
```



Candlestick chart It describes open, high, low and close for a given bitcoin price per day. The boxes represent the spread between the open and close values and the lines represent the spread between the low and high values. Sample points where the close value is higher (lower) then the open value are called increasing (decreasing). By default, increasing candles are drawn in green whereas decreasing are drawn in red.

[122]:
```
fig = go.Figure(data=[go.Candlestick(x=data['Date'],
                open=data['Open'],
                high=data['High'],
                low=data['Low'],
                close=data['Price'])])

fig.show()
```

1.0.4 Ideas for the next phase

Architecture We're planning to implement a Deep Q-network with 4 layers in total(two are hidden), with the number of units set to approximately 90, 100, 100, and 3 respectively.

Input: The input units were composed by the delta price (difference between two consecutive days) of the bitcoin price chart **Output**: The output units correspond to the three actions in trading namely: Buy, Hold, and Sell.

Implementation overview We will consider a simple trading task that operates on a single security, and at each trading day t, only one action will be allowed. The action at a_t will have 3 options: hold, buy, or sell and a reward r_t will be obtained. Our task will be to learn a deep Q-function $Q(s, a)$ that maximizes the long term accumulated profit. No transaction cost will be considered in this project.

The environment will mimic the OpenAI gym infrastructure. We intend to write our Artificial Neural Network in Keras. Pandas and Spark was used for data preprocessing and cleaning. Data visualization will be done using the matplotlib library and the model will be evaluated based on parameters like loss and reward generated during training.

1.0.5 Acknowledgments

- http://cslt.riit.tsinghua.edu.cn/mediawiki/images/5/5f/Dtq.pdf

[ ]:

```
```