Stock_Qlearning

August 3, 2020

0.1 Deep learning/Reinforcement learning in Time series data: Stock price verion

Our goal is to predict close price using our model from previous input Episode one: https://www.kaggle.com/peraktong/transformer-ts Please let me know if you have any question. Thanks to this useful link : https://www.tensorflow.org/tutorials/text/transformer Thanks to this useful link: https://www.kaggle.com/itoeiji/deep-reinforcement-learning-on-stock-data Thanks to this useful link: https://towardsdatascience.com/aifortrading-2edd6fac689d Thanks to this useful link: https://www.tensorflow.org/agents/tutorials/1_dqn_tutorial Thanks to this useful link: https://rubikscode.net/2019/07/08/deep-q-learning-with-python-and-tensorflow-2-0/

```
In [1]: import numpy as np # linear algebra
        import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
        import matplotlib
        import tensorflow as tf
        from matplotlib import colors as mcolors
        import matplotlib.pyplot as plt
        color_array = list(mcolors.CSS4_COLORS.keys())
        # Input data files are available in the read-only "../input/" directory
        # For example, running this (by clicking run or pressing Shift+Enter) will list all fi

        import os
        names_list = []
        for dirname, _, filenames in os.walk('Data/Stocks/'):
            for filename in filenames:
                #print(os.path.join(dirname, filename))

                names_list.append(filename)
        names_list = np.array(names_list)


        # TPU session :)
        # detect and init the TPU
        if False:
            tpu = tf.distribute.cluster_resolver.TPUClusterResolver()
            tf.config.experimental_connect_to_cluster(tpu)
            tf.tpu.experimental.initialize_tpu_system(tpu)
```

```
    # instantiate a distribution strategy
    tpu_strategy = tf.distribute.experimental.TPUStrategy(tpu)
```

In [2]:
```
root_path = 'Data/Stocks/'
#root_path = "/kaggle/input/price-volume-data-for-all-us-stocks-etfs/ETFs/"

df = pd.read_csv(root_path + "googl.us.txt")
```

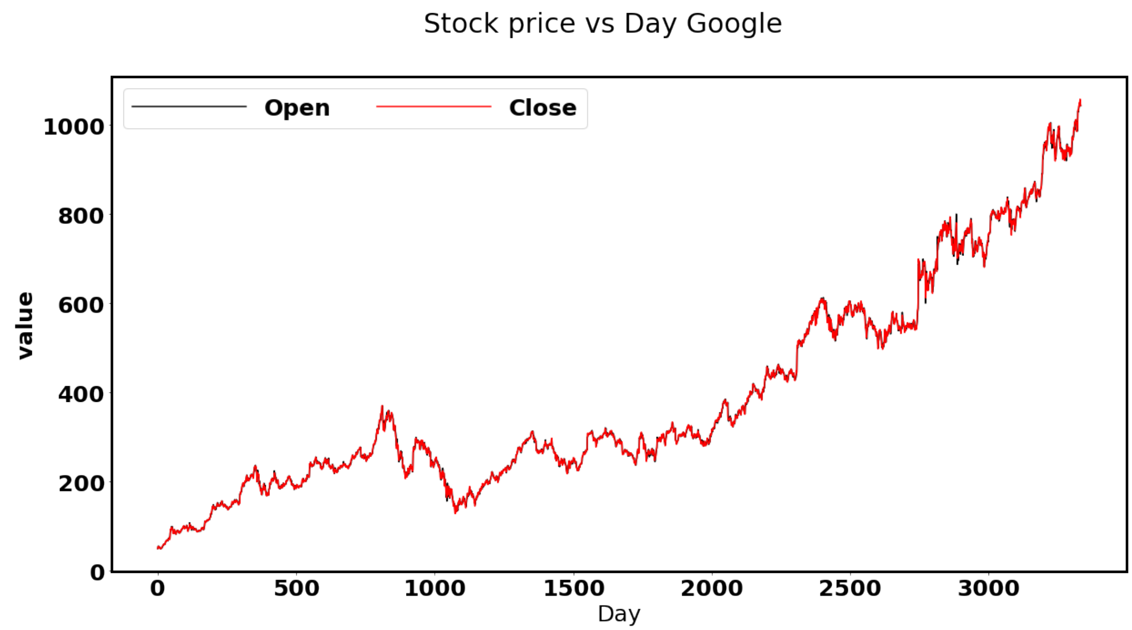
In [3]:
```
df.head()
```

Out[3]:

	Date	Open	High	Low	Close	Volume	OpenInt
0	2004-08-19	50.000	52.03	47.980	50.170	44703800	0
1	2004-08-20	50.505	54.54	50.250	54.155	22857200	0
2	2004-08-23	55.375	56.74	54.525	54.700	18274400	0
3	2004-08-24	55.620	55.80	51.785	52.435	15262600	0
4	2004-08-25	52.480	54.00	51.940	53.000	9197800	0

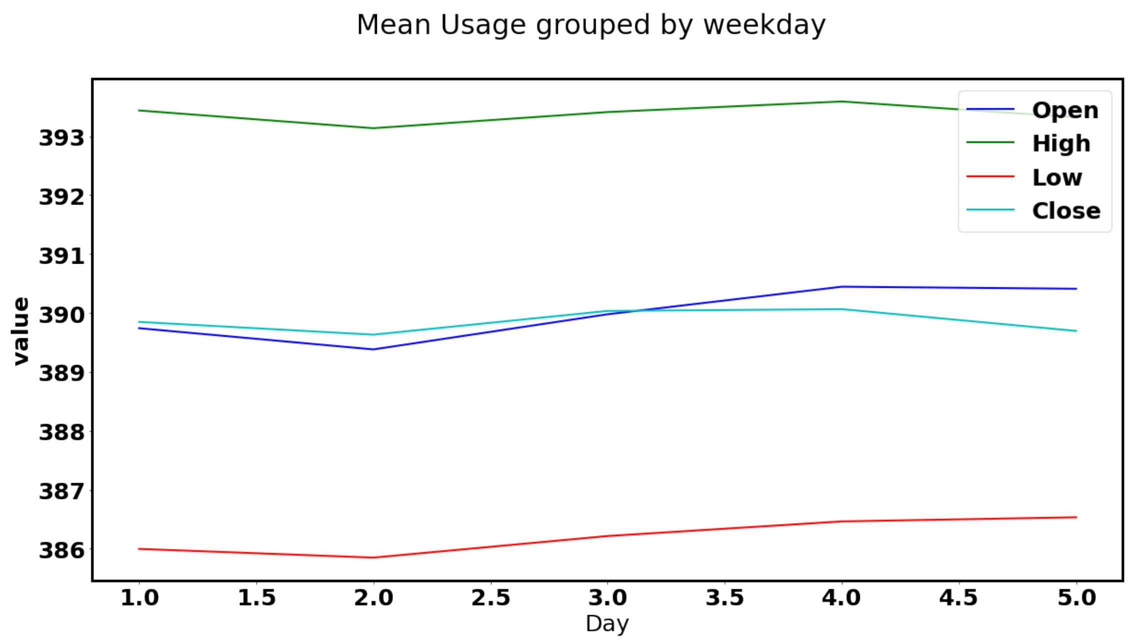
In [4]:
```
import matplotlib
from matplotlib.pylab import rc
font = {'family': 'normal','weight': 'bold',
        'size': 25}

matplotlib.rc('font', **font)
rc('axes', linewidth=3)


plt.subplot(1,1,1)
plt.plot(df["Open"],"k",label="Open")
plt.plot(df["Close"],"r",label="Close")


plt.xlabel("Day")
plt.ylabel(r"${\rm value}$")
plt.suptitle("Stock price vs Day Google")

fig = matplotlib.pyplot.gcf()

fig.set_size_inches(20,10)
plt.legend(fontsize=25,handlelength=5,ncol=3)
plt.show()
```

```
findfont: Font family ['normal'] not found. Falling back to DejaVu Sans.
findfont: Font family ['normal'] not found. Falling back to DejaVu Sans.
findfont: Font family ['normal'] not found. Falling back to DejaVu Sans.
```



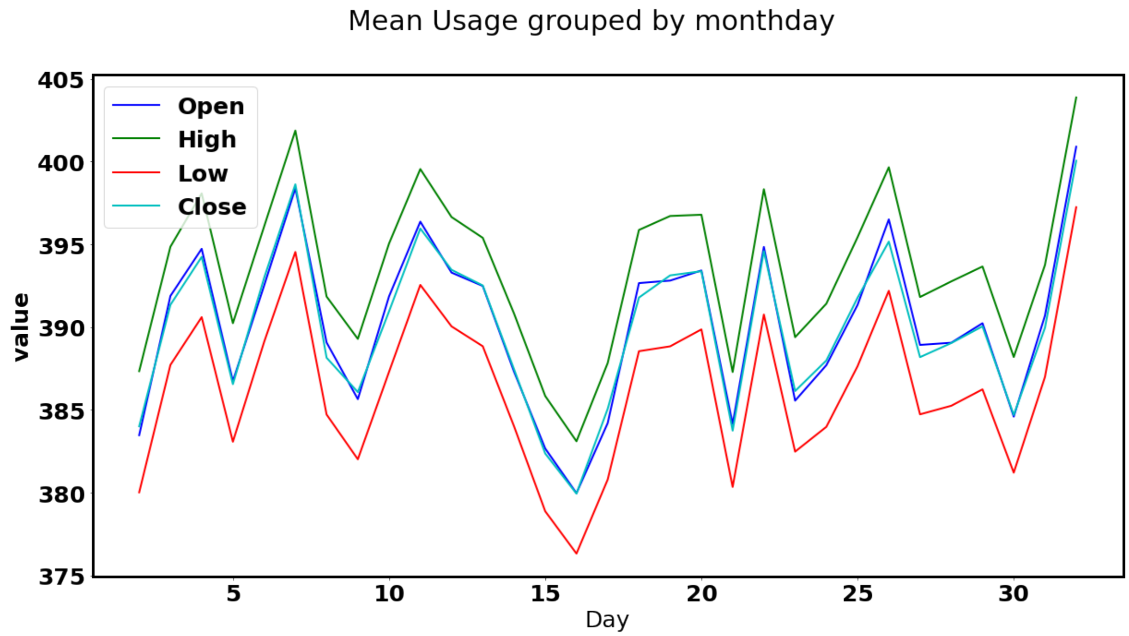
In [5]:
```
# Let's check whether there is a peroid in week/month?
import datetime
df['Date'] = pd.to_datetime(df['Date'], errors='coerce')
df['weekday'] = df['Date'].dt.weekday
df['monthday'] = df['Date'].dt.day
df['month'] = df['Date'].dt.month

from matplotlib.pylab import rc
font = {'family': 'normal','weight': 'bold',
        'size': 25}

matplotlib.rc('font', **font)
rc('axes', linewidth=3)

color_array = ['b', 'g', 'r', 'c', 'm', 'y', 'k']

plt.subplot(1,1,1)


names_array = list(df.keys()[1:5])
for i in range(len(names_array)):
    #print("Doing %d"%i)
    plt.plot(df.groupby('weekday').mean().index+1,df.groupby('weekday').mean()[names_a
```

```
plt.xlabel("Day")
plt.ylabel(r"${\rm value}$")
plt.suptitle("Mean Usage grouped by weekday")

fig = matplotlib.pyplot.gcf()

fig.set_size_inches(20,10)
plt.legend()
plt.show()
```



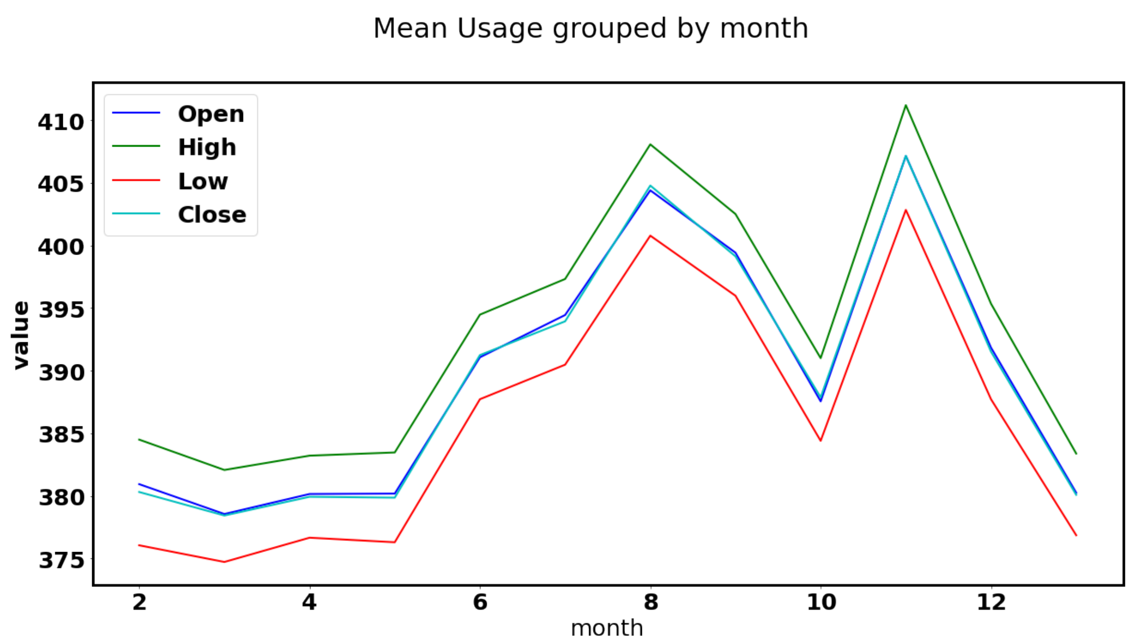

```
In [6]: from matplotlib.pylab import rc
        font = {'family': 'normal','weight': 'bold',
                'size': 25}

        matplotlib.rc('font', **font)
        rc('axes', linewidth=3)

        color_array = ['b', 'g', 'r', 'c', 'm', 'y', 'k']

        plt.subplot(1,1,1)


        names_array = list(df.keys()[1:5])
        for i in range(len(names_array)):
            #print("Doing %d"%i)
            plt.plot(df.groupby('monthday').mean().index+1,df.groupby('monthday').mean()[names_
```

```
plt.xlabel("Day")
plt.ylabel(r"${\rm value}$")
plt.suptitle("Mean Usage grouped by monthday")

fig = matplotlib.pyplot.gcf()

fig.set_size_inches(20,10)
plt.legend()
plt.show()
```




```
In [7]: # By month?


        from matplotlib.pylab import rc
        font = {'family': 'normal','weight': 'bold',
                'size': 25}

        matplotlib.rc('font', **font)
        rc('axes', linewidth=3)

        color_array = ['b', 'g', 'r', 'c', 'm', 'y', 'k']
```

```
plt.subplot(1,1,1)


names_array = list(df.keys()[1:5])
for i in range(len(names_array)):
    #print("Doing %d"%i)
    plt.plot(df.groupby('month').mean().index+1,df.groupby('month').mean()[names_array




plt.xlabel("month")
plt.ylabel(r"${\rm value}$")
plt.suptitle("Mean Usage grouped by month")

fig = matplotlib.pyplot.gcf()

fig.set_size_inches(20,10)
plt.legend()
plt.show()
```



1 baseline model: GRU+Dense layer structure:

```
In [12]: from sklearn import preprocessing
         from keras.models import Model
```

```python
from sklearn.preprocessing import LabelEncoder
import tensorflow as tf
from keras.layers import Input,Masking,Dense,GRU
from sklearn.model_selection import train_test_split
from keras.layers import Dropout
```

In [13]:
```python
# some hyper parameters
# Here we use 30 day data to predict future stock price. May need to modify later
delta_t = 30
n_cell = 50
dropout_rate= 0.1
n_epoch=30
batch=256
```

In [14]:
```python
checkpoint_path = "model/cp.ckpt"
checkpoint_dir = os.path.dirname(checkpoint_path)

min_max_scaler = preprocessing.StandardScaler()

# min-max scaler
np_scaled = min_max_scaler.fit_transform(df[names_array])

df_scaled = pd.DataFrame(np_scaled,columns=names_array)


X = np.zeros((df_scaled.shape[0]-delta_t,delta_t,len(names_array)),dtype=float)
y = df_scaled["Close"][delta_t:]


for i in range(len(y)):
    if i%800==0:
        print("Prepare data %.2f percent"%(100*i/len(y)))
    X[i,:,:] = df_scaled[i:i+delta_t][names_array].values

# split train test:
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shuffle=True)
```

```
Prepare data 0.00 percent
Prepare data 24.22 percent
Prepare data 48.44 percent
Prepare data 72.66 percent
Prepare data 96.88 percent
```

In [15]:
```python
def generate_model(MAX_TIMESTEPS,MAX_NB_VARIABLES):
    ip = Input(shape=(MAX_TIMESTEPS,MAX_NB_VARIABLES))
    # split into x and y two channels

    x = Masking()(ip)
```

```
        x = GRU(n_cell)(x)

        out = Dense(1)(x)
        #out = Dropout(dropout_rate)(x)
        #loc, scale = tf.keras.layers.GaussianNoise(stddev=0.01)(out)

        # now we only output loc
        #out=loc

        model = Model(ip, out)
        model.summary()

        # add load model code here to fine-tune

        return model

    model = generate_model(delta_t,X.shape[2])
    model.compile(loss='mae', optimizer='adam')
    #model.summary()

    callback = tf.keras.callbacks.ModelCheckpoint(filepath=checkpoint_path,
                                                  save_weights_only=True,
                                                  verbose=1)
```

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 30, 4)]           0
_________________________________________________________________
masking (Masking)            (None, 30, 4)             0
_________________________________________________________________
gru (GRU)                    (None, 50)                8400
_________________________________________________________________
dense (Dense)                (None, 1)                 51
=================================================================
Total params: 8,451
Trainable params: 8,451
Non-trainable params: 0
_________________________________________________________________
```

```
In [16]: history = model.fit(X_train, y_train, epochs=n_epoch, batch_size=batch, validation_da
```

```
Epoch 1/30

Epoch 00001: saving model to model/cp.ckpt
10/10 - 2s - loss: 0.6025 - val_loss: 0.2666
```

```
Epoch 2/30

Epoch 00002: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.1754 - val_loss: 0.1587
Epoch 3/30

Epoch 00003: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.1070 - val_loss: 0.0618
Epoch 4/30

Epoch 00004: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0652 - val_loss: 0.0540
Epoch 5/30

Epoch 00005: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0576 - val_loss: 0.0427
Epoch 6/30

Epoch 00006: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0432 - val_loss: 0.0430
Epoch 7/30

Epoch 00007: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0424 - val_loss: 0.0387
Epoch 8/30

Epoch 00008: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0363 - val_loss: 0.0361
Epoch 9/30

Epoch 00009: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0341 - val_loss: 0.0319
Epoch 10/30

Epoch 00010: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0315 - val_loss: 0.0302
Epoch 11/30

Epoch 00011: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0292 - val_loss: 0.0283
Epoch 12/30

Epoch 00012: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0275 - val_loss: 0.0268
Epoch 13/30

Epoch 00013: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0261 - val_loss: 0.0257
```

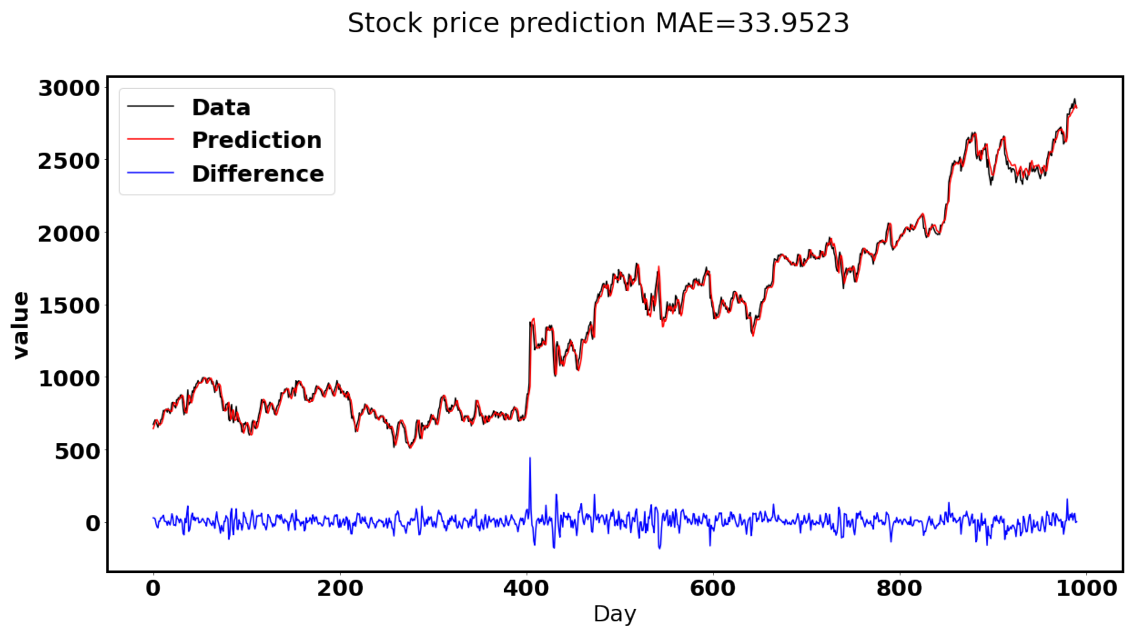
```
Epoch 14/30

Epoch 00014: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0256 - val_loss: 0.0252
Epoch 15/30

Epoch 00015: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0257 - val_loss: 0.0255
Epoch 16/30

Epoch 00016: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0266 - val_loss: 0.0257
Epoch 17/30

Epoch 00017: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0270 - val_loss: 0.0249
Epoch 18/30

Epoch 00018: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0269 - val_loss: 0.0241
Epoch 19/30

Epoch 00019: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0261 - val_loss: 0.0240
Epoch 20/30

Epoch 00020: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0253 - val_loss: 0.0239
Epoch 21/30

Epoch 00021: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0250 - val_loss: 0.0240
Epoch 22/30

Epoch 00022: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0255 - val_loss: 0.0238
Epoch 23/30

Epoch 00023: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0257 - val_loss: 0.0236
Epoch 24/30

Epoch 00024: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0256 - val_loss: 0.0235
Epoch 25/30

Epoch 00025: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0252 - val_loss: 0.0236
```

```
Epoch 26/30

Epoch 00026: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0249 - val_loss: 0.0233
Epoch 27/30

Epoch 00027: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0251 - val_loss: 0.0233
Epoch 28/30

Epoch 00028: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0249 - val_loss: 0.0232
Epoch 29/30

Epoch 00029: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0248 - val_loss: 0.0233
Epoch 30/30

Epoch 00030: saving model to model/cp.ckpt
10/10 - 0s - loss: 0.0245 - val_loss: 0.0231
```

In [17]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shuffle=False
y_pre = model.predict(X_test)
```

In [19]:
```
from matplotlib.pylab import rc
font = {'family': 'normal','weight': 'bold',
        'size': 25}

matplotlib.rc('font', **font)
rc('axes', linewidth=3)

color_array = ['b', 'g', 'r', 'c', 'm', 'y', 'k']

plt.subplot(1,1,1)

min_val = np.nanmin(df["Close"])
max_val = np.nanmax(df["Close"])



date_array = np.arange(0,len(y_test),1)

y1 = min_val+(max_val-min_val)*y_test
y2 = min_val+(max_val-min_val)*y_pre[:,0]
plt.plot(date_array,y1,"k",label = "Data")
plt.plot(date_array,y2,"r",label = "Prediction")
plt.plot(date_array,y1-y2,"b",label = "Difference")
```

```
plt.xlabel("Day")
plt.ylabel(r"${\rm value}$")
plt.suptitle("Stock price prediction MAE=%.4f"%np.nanmean(abs(y1-y2)))

fig = matplotlib.pyplot.gcf()

fig.set_size_inches(20,10)
plt.legend()
plt.show()
```



1.1 The prediction seems to have a "Latency" inside.

1.2 Let's try the Q-net

In Q-learning we learn the value of taking an action from a given state. Q-value is the expected return after taking the action. We will use Rainbow which is a combination of seven Q learning algorithms.

```
In [8]: class Environment1:

            def __init__(self, data, history_t=90):
                self.data = data
                self.history_t = history_t
                self.reset()

            def reset(self):
                self.t = 0
```

```
            self.done = False
            self.profits = 0
            self.positions = []
            self.position_value = 0
            self.history = [0 for _ in range(self.history_t)]
            return [self.position_value] + self.history # obs

        def step(self, act):
            reward = 0

            # act = 0: stay, 1: buy, 2: sell
            if act == 1:
                self.positions.append(self.data.iloc[self.t, :]['Close'])
            elif act == 2: # sell
                if len(self.positions) == 0:
                    reward = -1
                else:
                    profits = 0
                    for p in self.positions:
                        profits += (self.data.iloc[self.t, :]['Close'] - p)
                    reward += profits
                    self.profits += profits
                    self.positions = []

            # set next time
            self.t += 1
            self.position_value = 0
            for p in self.positions:
                self.position_value += (self.data.iloc[self.t, :]['Close'] - p)
            self.history.pop(0)
            self.history.append(self.data.iloc[self.t, :]['Close'] - self.data.iloc[(self.t

            # clipping reward
            if reward > 0:
                reward = 1
            elif reward < 0:
                reward = -1

            return [self.position_value] + self.history, reward, self.done
```

In [9]:
```
df = pd.read_csv(root_path + "googl.us.txt")
df['Date'] = pd.to_datetime(df['Date'])
data = df.set_index('Date')

env = Environment1(df)
print(env.reset())
for _ in range(3):
    pact = np.random.randint(3)
```

```
            #print(env.step(pact))
```

```
[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, (
```

```
In [10]: delta_split = int(df.shape[0]*0.7)

         train = df[:delta_split]
         test = df[delta_split:]
         print("Training date length",len(train),"testing date length", len(test))
```

```
Training date length 2333 testing date length 1000
```

```
In [12]: import chainer
         import chainer.functions as F
         import chainer.links as L
         import copy
         import time



         def train_dqn(env):

             class Q_Network(chainer.Chain):

                 def __init__(self, input_size, hidden_size, output_size):
                     super(Q_Network, self).__init__(
                         fc1 = L.Linear(input_size, hidden_size),
                         fc2 = L.Linear(hidden_size, hidden_size),
                         fc3 = L.Linear(hidden_size, output_size)
                     )

                 def __call__(self, x):
                     h = F.relu(self.fc1(x))
                     h = F.relu(self.fc2(h))
                     y = self.fc3(h)
                     return y

                 def reset(self):
                     self.zerograds()

             Q = Q_Network(input_size=env.history_t+1, hidden_size=100, output_size=3)
             # GPU Option
             #Q.to_gpu()

             Q_ast = copy.deepcopy(Q)
             optimizer = chainer.optimizers.Adam()
             optimizer.setup(Q)
```

```python
# Hyper-parameters
epoch_num = 80
step_max = len(env.data)-1
memory_size = 200
batch_size = 20
epsilon = 1.0
epsilon_decrease = 1e-3
epsilon_min = 0.1
start_reduce_epsilon = 200
train_freq = 10
update_q_freq = 20
gamma = 0.97
show_log_freq = 5


memory = []
total_step = 0
total_rewards = []
total_losses = []

start = time.time()
for epoch in range(epoch_num):

    pobs = env.reset()
    step = 0
    done = False
    total_reward = 0
    total_loss = 0

    while not done and step < step_max:

        # select act
        pact = np.random.randint(3)
        if np.random.rand() > epsilon:
            pact = Q(np.array(pobs, dtype=np.float32).reshape(1, -1))
            pact = np.argmax(pact.data)

        # act
        obs, reward, done = env.step(pact)

        # add memory
        memory.append((pobs, pact, reward, obs, done))
        if len(memory) > memory_size:
            memory.pop(0)

        # train or update q
        if len(memory) == memory_size:
```

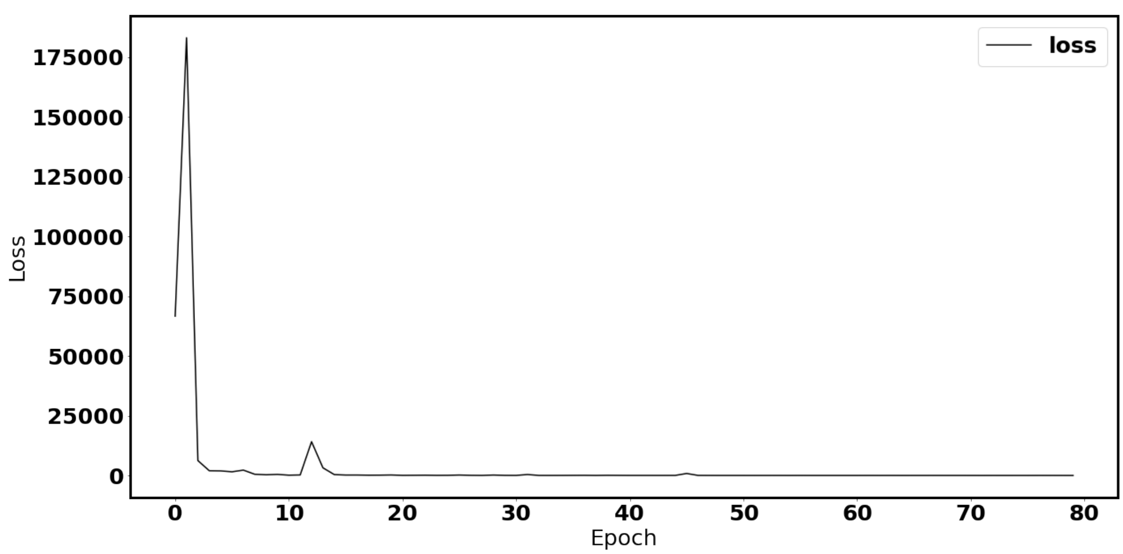
```
                if total_step % train_freq == 0:
                    shuffled_memory = np.random.permutation(memory)
                    memory_idx = range(len(shuffled_memory))
                    for i in memory_idx[::batch_size]:
                        batch = np.array(shuffled_memory[i:i+batch_size])
                        b_pobs = np.array(batch[:, 0].tolist(), dtype=np.float32).resh
                        b_pact = np.array(batch[:, 1].tolist(), dtype=np.int32)
                        b_reward = np.array(batch[:, 2].tolist(), dtype=np.int32)
                        b_obs = np.array(batch[:, 3].tolist(), dtype=np.float32).resha
                        b_done = np.array(batch[:, 4].tolist(), dtype=np.bool)

                        q = Q(b_pobs)
                        maxq = np.max(Q_ast(b_obs).data, axis=1)
                        target = copy.deepcopy(q.data)
                        for j in range(batch_size):
                            target[j, b_pact[j]] = b_reward[j]+gamma*maxq[j]*(not b_do
                        Q.reset()
                        loss = F.mean_squared_error(q, target)
                        total_loss += loss.data
                        loss.backward()
                        optimizer.update()

                if total_step % update_q_freq == 0:
                    Q_ast = copy.deepcopy(Q)

            # epsilon
            if epsilon > epsilon_min and total_step > start_reduce_epsilon:
                epsilon -= epsilon_decrease

            # next step
            total_reward += reward
            pobs = obs
            step += 1
            total_step += 1

        total_rewards.append(total_reward)
        total_losses.append(total_loss)

        if (epoch+1) % show_log_freq == 0:
            log_reward = sum(total_rewards[((epoch+1)-show_log_freq):])/show_log_freq
            log_loss = sum(total_losses[((epoch+1)-show_log_freq):])/show_log_freq
            elapsed_time = time.time()-start
            print('\t'.join(map(str, [epoch+1, epsilon, total_step, log_reward, log_lo
            start = time.time()

    return Q, total_losses, total_rewards
```

```
In [13]: # Let's do it!
```

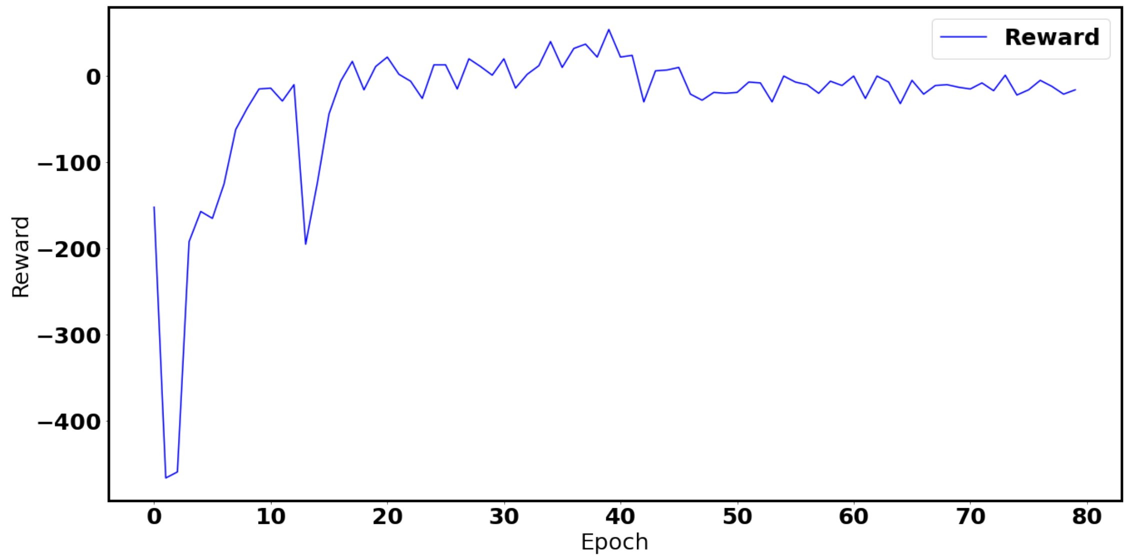
```
Q, total_losses, total_rewards = train_dqn(Environment1(train))
```

```
5         0.0999999999999992        11660        -285.2        51965.05232162122        117.4800
10         0.0999999999999992        23320        -80.8        1027.4448142735287        115.840
15         0.0999999999999992        34980        -74.4        3630.1065551162233        119.920
20         0.0999999999999992        46640        -7.6        185.28804305889645        116.4130
25         0.0999999999999992        58300        1.0        94.8101543105673        125.799100
30         0.0999999999999992        69960        6.0        120.34398262030444        120.1654
35         0.0999999999999992        81620        12.0        119.88713874976384        122.615
40         0.0999999999999992        93280        31.0        67.79507062511402        144.3807
45         0.0999999999999992        104940        5.8        44.29382843388188        156.4024
50         0.0999999999999992        116600        -15.6        201.66404752623004        173.08
55         0.0999999999999992        128260        -12.8        28.744812113972795        161.46
60         0.0999999999999992        139920        -10.8        27.08253281260819        146.280
65         0.0999999999999992        151580        -13.0        29.144518221883402        172.47
70         0.0999999999999992        163240        -12.0        30.49970243915491        149.457
75         0.0999999999999992        174900        -12.2        24.998096223475294        139.92
80         0.0999999999999992        186560        -14.0        29.336842975529276        157.92
```

In [16]:
```
plt.plot(total_losses,"k",label="loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")

fig = matplotlib.pyplot.gcf()

fig.set_size_inches(20,10)
plt.legend()
plt.show()
```



In [18]:
```
plt.plot(total_rewards,"b",label="Reward")
plt.xlabel("Epoch")
plt.ylabel("Reward")

fig = matplotlib.pyplot.gcf()

fig.set_size_inches(20,10)
plt.legend()
plt.show()
```

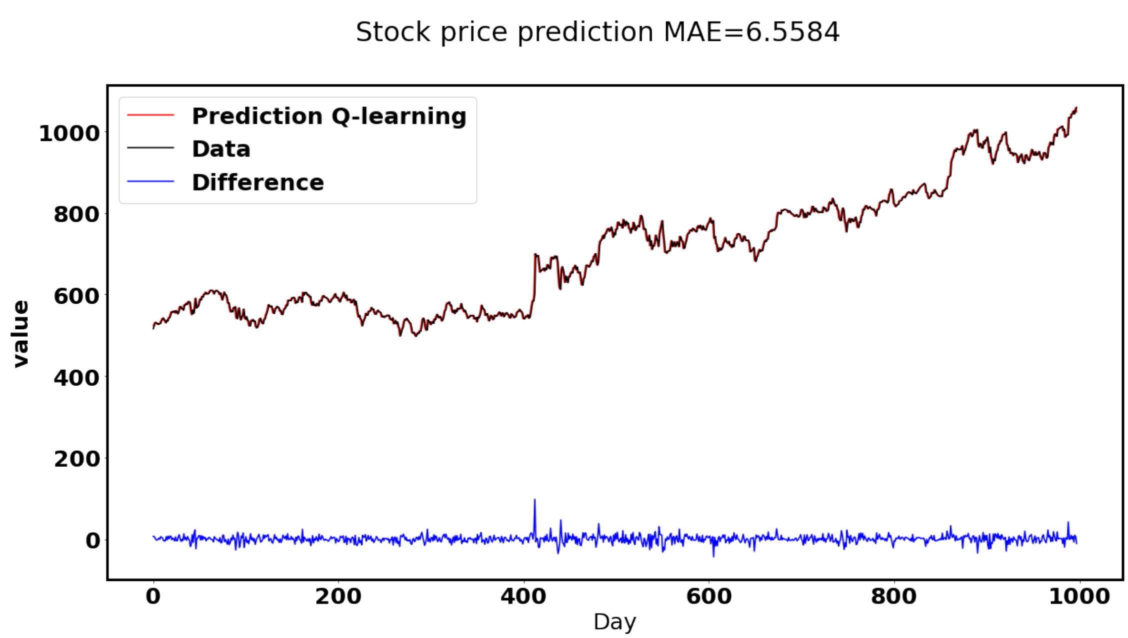


In [30]:
```
train_env,test_env = Environment1(train), Environment1(test)

# train
pobs = train_env.reset()
train_acts = []
train_rewards = []

for _ in range(len(train_env.data) - 1):
    pact = Q(np.array(pobs, dtype=np.float32).reshape(1, -1))
    pact = np.argmax(pact.data)
    train_acts.append(pact)

    obs, reward, done = train_env.step(pact)
    train_rewards.append(reward)

    pobs = obs

train_profits = train_env.profits
```

```python
# test
pobs = test_env.reset()
test_acts = []
test_rewards = []

for _ in range(len(test_env.data) - 1):
    pact = Q(np.array(pobs, dtype=np.float32).reshape(1, -1))
    pact = np.argmax(pact.data)
    test_acts.append(pact)

    obs, reward, done = test_env.step(pact)
    test_rewards.append(reward)

    pobs = obs

test_profits = test_env.profits
pobs = train_env.reset()
train_acts = []
train_rewards = []

for _ in range(len(train_env.data) - 1):
    pact = Q(np.array(pobs, dtype=np.float32).reshape(1, -1))
    pact = np.argmax(pact.data)
    train_acts.append(pact)

    obs, reward, done = train_env.step(pact)
    train_rewards.append(reward)

    pobs = obs

train_profits = train_env.profits

# test
pobs = test_env.reset()
test_acts = []
test_rewards = []

for _ in range(len(test_env.data) - 1):
    pact = Q(np.array(pobs, dtype=np.float32).reshape(1, -1))
    pact = np.argmax(pact.data)
    test_acts.append(pact)

    obs, reward, done = test_env.step(pact)
    test_rewards.append(reward)

    pobs = obs

test_profits = test_env.profits
```

In [43]:
```
train_copy = train_env.data.copy()
test_copy = test_env.data.copy()
train_copy['act'] = train_acts + [np.nan]
train_copy['reward'] = train_rewards + [np.nan]
test_copy['act'] = test_acts + [np.nan]
test_copy['reward'] = test_rewards + [np.nan]
train0 = train_copy[train_copy['act'] == 0]
train1 = train_copy[train_copy['act'] == 1]
train2 = train_copy[train_copy['act'] == 2]
test0 = test_copy[test_copy['act'] == 0]
test1 = test_copy[test_copy['act'] == 1]
test2 = test_copy[test_copy['act'] == 2]
```

In [82]:
```
y1 = test0['Close']
y2 = test["Close"]
y2 = y2[:len(y1)].values

plt.plot(np.arange(0,len(y1),1),y1,"r",label="Prediction Q-learning")
plt.plot(np.arange(0,len(y1),1),y2,"k",label="Data")
plt.plot(np.arange(0,len(y1),1),y1-y2,"b",label="Difference")
plt.xlabel("Day")
plt.ylabel(r"${\rm value}$")
plt.suptitle("Stock price prediction MAE=%.4f"%np.nanmean(abs(y1-y2[:len(y1)])))

fig = matplotlib.pyplot.gcf()

fig.set_size_inches(20,10)
plt.legend()
plt.show()
```



```
In [ ]:
```

```
In [ ]:
```

```
In [ ]:
```