The main ideal in this project is that, combining with the Carhart four-factor model, we add many other momemtum factors which take different time periods. By using PCA, we then deduce the dimensionality, and construct our positions and apply the strategy. We would gain a time series of daily returns, and finally try to establish a LSTM model on it.

The first step is to realize the Carhart four-factor model.

In [1]:

```
import warnings
warnings.filterwarnings("ignore")
import akshare as ak
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import datetime
import QUANTAXIS as QA
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
import tensorflow as tf
from sklearn import linear_model
from sklearn.metrics import mean_absolute_error
import plotly
import os
import random
import statsmodels.tsa.seasonal as smt
from subprocess import check_output
# import the relevant Keras modules
from keras.models import Sequential
from keras.layers import Activation, Dense
from keras.layers import LSTM
from keras.layers import Dropout
```

1. Read data files

In [2]:

```
close_df = pd.read_csv("C:\\Users\\tianj\\Project 1\\data\\HS300_data\\close.csv",
                       index_col = "trade_date")
return_df = pd.read_csv("C:\\Users\\tianj\\Project 1\\data\\HS300_data\\return.csv",
                        index_col = "trade_date")
BM_df = pd.read_csv("C:\\Users\\tianj\\Project 1\\data\\HS300_data\\BM.csv",
                    index_col = "trade_date")
MV_df = pd.read_csv("C:\\Users\\tianj\\Project 1\\data\\HS300_data\\MV.csv",
                    index_col = "trade_date")

# Convert interest rates
return_df = return_df / 100
```

In [3]:

```
# datetime conversion
close_df.index = pd.to_datetime(close_df.index)
return_df.index = pd.to_datetime(return_df.index)
BM_df.index = pd.to_datetime(BM_df.index)
MV_df.index = pd.to_datetime(MV_df.index)
```

In [4]:

```
deposit_interest_rate = pd.read_csv(
    "C:\\Users\\tianj\\Project 1\\data\\HS300_data\\deposit_interest_rate.csv",
    encoding = "gbk").fillna(method = "ffill")[["pubDate", "fixedDepositRate3Month"]]

central_bank_bill = pd.read_csv(
    "C:\\Users\\tianj\\Project 1\\data\\HS300_data\\central_bank_bill.csv",
    encoding = "gbk").fillna(method = "ffill")[["short_name", "list_date"]]

shibor = pd.read_csv(
    "C:\\Users\\tianj\\Project 1\\data\\HS300_data\\shibor.csv",
    encoding = "gbk").fillna(method = "ffill")
```

2. Interest retes conversions.

Time(t)	Sources
$t \le$ 2002-08-06	Three-month fixed deposit rates
2002-08-07 $\le t \le$ 2006-10-07	Coupon rate of three-month central bank bills
2006-10-08 $\le t$	Shibor

In [5]:

```
deposit_interest_rate = deposit_interest_rate.rename(columns = {"fixedDepositRate3Month": "rate
                                                                "pubDate": "date"})

deposit_interest_rate["date"] = pd.to_datetime(deposit_interest_rate["date"])

deposit_interest_rate["rate"] = (1 + deposit_interest_rate["rate"] / 100)**(1/91) - 1
```

In [6]:

```
central_bank_bill["list_date"] = pd.to_datetime(central_bank_bill["list_date"])
central_bank_bill["rate"] = None
central_bank_bill.rename(columns={"list_date": "date"}, inplace = True)
billLst = [['2003.04.30',2.1800],['2003.05.07',2.1500],['2003.05.14',2.1900],['2003.05.21',2.15
            ['2003.05.28',2.1900],['2003.06.04',2.1900],['2003.06.11',2.2300],['2003.06.18',2.27
            ['2003.06.25',2.3100],['2003.07.02',2.3100],['2003.07.09',2.3100],['2003.07.16',2.31
            ['2003.07.23',2.3100],['2003.07.30',2.3100],['2003.08.06',2.3100],['2003.08.13',2.27
            ['2003.08.20',2.3500],['2003.08.27',2.4300],['2003.09.03',2.6600],['2003.09.10',2.71
            ['2003.09.17',2.7100],['2003.09.24',2.6600],['2003.10.15',2.7200],['2003.10.22',2.68
            ['2003.10.29',2.7200],['2003.11.12',2.8000],['2003.11.19',2.7200],['2003.11.26',2.44
            ['2003.12.03',2.4600],['2003.12.10',2.4600],['2003.12.17',2.4600],['2003.12.24',2.46
            ['2003.12.31',2.4600],['2004.01.07',2.4600],['2004.01.14',2.4600],['2004.01.21',2.46
            ['2004.02.04',2.4600],['2004.02.11',2.3500],['2004.02.18',2.2700],['2004.02.25',2.06
            ['2004.03.03',1.9900],['2004.03.10',1.9100],['2004.03.17',1.8700],['2004.03.24',2.19
            ['2004.03.31',2.1100],['2004.04.07',2.1400],['2004.04.14',2.1400],['2004.05.19',2.80
            ['2004.05.26',2.7200],['2004.06.02',2.8000],['2004.06.23',2.8000],['2004.06.30',2.88
            ['2004.07.07',2.8400],['2004.07.14',2.8400],['2004.07.21',2.8800],['2004.08.06',2.86
            ['2004.08.13',2.8200],['2004.08.20',2.7400],['2004.08.27',2.6200],['2004.09.03',2.42
            ['2004.09.10',2.3000],['2004.09.17',2.4200],['2004.09.24',2.5000],['2004.09.29',2.42
            ['2004.10.15',2.4600],['2004.10.22',2.5400],['2004.10.29',2.5800],['2004.11.05',2.58
            ['2004.11.12',2.5300],['2004.11.19',2.5000],['2004.11.26',2.5000],['2004.12.03',2.46
            ['2004.12.10',2.1400],['2004.12.17',2.4600],['2004.12.24',2.6600],['2004.12.31',2.66
            ['2005.01.07',2.5800],['2005.01.14',2.5400],['2005.01.21',2.3800],['2005.02.18',2.38
            ['2005.02.25',2.2600],['2005.03.04',2.1800],['2005.03.11',2.0200],['2005.03.17',2.38
            ['2005.03.18',1.4500],['2005.03.25',1.2900],['2005.04.01',1.2100],['2005.04.08',1.17
            ['2005.04.15',1.0900],['2005.04.22',1.1700],['2005.04.29',1.0900],['2005.05.13',1.21
            ['2005.05.20',1.2100],['2005.05.27',1.2100],['2005.06.03',1.1700],['2005.06.10',1.09
            ['2005.06.17',1.0900],['2005.06.24',1.1700],['2005.07.01',1.2100],['2005.07.08',1.15
            ['2005.07.15',1.1300],['2005.07.22',1.1300],['2005.07.29',1.0900],['2005.08.05',1.09
            ['2005.08.12',1.0900],['2005.08.19',1.0500],['2005.08.26',1.0900],['2005.09.02',1.09
            ['2005.09.09',1.0900],['2005.09.16',1.1300],['2005.09.23',1.1700],['2005.09.30',1.17
            ['2005.10.14',1.1700],['2005.10.21',1.1700],['2005.10.28',1.1700],['2005.11.04',1.22
            ['2005.11.11',1.3700],['2005.11.18',1.4900],['2005.11.25',1.6100],['2005.12.02',1.81
            ['2006.02.10',1.7300],['2006.02.17',1.7300],['2006.02.24',1.7700],['2006.03.03',1.73
            ['2006.03.10',1.7300],['2006.03.24',1.7700],['2006.03.31',1.8100],['2006.04.07',1.81
            ['2006.04.14',1.8500],['2006.04.21',1.8900],['2006.04.28',1.9800],['2006.05.12',2.02
            ['2006.05.19',2.0200],['2006.05.26',2.0600],['2006.06.02',2.1000],['2006.06.09',2.14
            ['2006.06.16',2.1800],['2006.06.23',2.2600],['2006.06.30',2.3400],['2006.07.07',2.37
            ['2006.07.14',2.3800],['2006.07.21',2.3800],['2006.07.28',2.3800],['2006.08.04',2.42
            ['2006.08.11',2.4200],['2006.08.18',2.5000],['2006.08.25',2.5400],['2006.09.01',2.54
            ['2006.09.08',2.5000],['2006.09.15',2.4600],['2006.09.22',2.4600],['2006.09.29',2.46
            ['2006.10.13',2.5000]]

billLst = list(zip(*zip(list(map(lambda x: x[0],billLst)), list(map(lambda x: x[1],billLst)))
billLst = pd.DataFrame(billLst[0], index = billLst[1]).reset_index()
billLst = billLst.rename(columns={"index": "rate", 0: "date"})
billLst["date"] = pd.to_datetime(billLst["date"])
central_bank_bill = pd.merge(central_bank_bill, billLst, how = "inner", on="date")
del central_bank_bill["rate_x"], central_bank_bill["short_name"]
central_bank_bill = central_bank_bill.rename(columns = {"rate_y": "rate"})
central_bank_bill.iloc[0, 0] = pd.to_datetime("2002-08-07")

central_bank_bill["rate"] = (1 + central_bank_bill["rate"] / 100)**(1/91) - 1
```

In [7]:

```
central_bank_bill
```

Out[7]:

	date	rate
0	2002-08-07	0.000310
1	2004-08-13	0.000306
2	2004-08-20	0.000297
3	2004-08-27	0.000284
4	2004-09-03	0.000263
...	...	...
93	2006-09-08	0.000271
94	2006-09-15	0.000267
95	2006-09-22	0.000267
96	2006-09-29	0.000267
97	2006-10-13	0.000271

98 rows × 2 columns

In [8]:

```
shibor = shibor[["date", "shibor3M"]].rename(columns = {"shibor3M": "rate"})
shibor["date"] = pd.to_datetime(shibor["date"].values)
shibor.iloc[-1, 0] = pd.to_datetime("2021-12-31")

shibor["rate"] = (1 + shibor["rate"] / 100)**(1/91) - 1
```

3. Setting parameters

In [9]:

```
startDate, endDate = "19950101", "20211231"

if int(startDate) > int(endDate) or int(endDate) > datetime.date.today().year * 10000 + \
        datetime.date.today().month * 100 + datetime.date.today().day:
    print("Invalid Time Interval")
    quit()
```

In [10]:

```
tradePercent = 0.1

laggedPeriod = pd.Timedelta("30 D")
windowPeriod = pd.Timedelta(str(30 * 11) + " D")
holdPeriod = pd.Timedelta("30 D")
```

In [11]:

```
def GetTradeCalender(start: str, end: str) -> pd.Series:
    cal = ak.tool_trade_date_hist_sina()
    return cal["trade_date"][
        (datetime.date(int(start[:4]),int(start[4:6]), int(start[6:])) <= cal["trade_date"]) &
        (cal["trade_date"] <= datetime.date(int(end[:4]), int(end[4:6]), int(end[6:])))]

calender = pd.to_datetime(GetTradeCalender(startDate, endDate))
```

Choose starting date

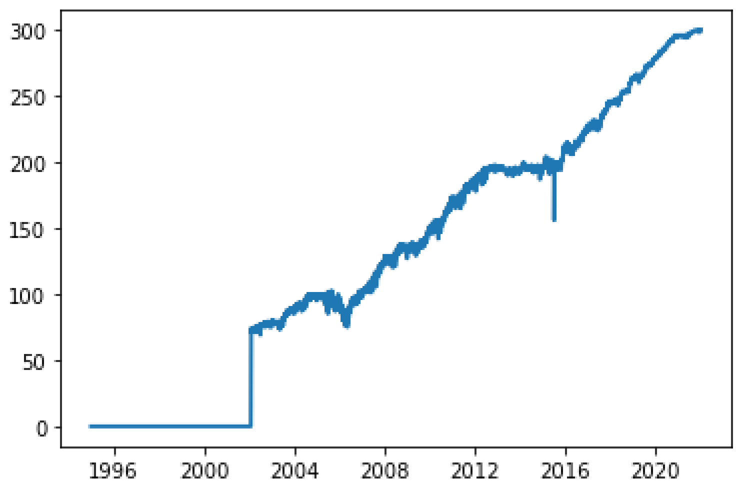
In [12]:

```
def CountValidData(row):
    return len(row) - sum(pd.isnull(row))

dailyValidData = pd.Series(list(map(min, close_df.apply(CountValidData, axis = 1),
                                    return_df.apply(CountValidData, axis = 1),
                                    BM_df.apply(CountValidData, axis = 1),
                                    MV_df.apply(CountValidData, axis = 1))),
                           index = calender.values, name = "trade_date")
```

In [13]:

```
print(plt.plot(dailyValidData.index, dailyValidData.values, ls="-", lw=2, label = "Valid Data A
```

```
[<matplotlib.lines.Line2D object at 0x0000023457584F40>]
```



According to the plot, we may change our start date from 2012-01-01 in our final step, since when the data were becoming sufficient for conducting analysis, however, for now we just change it to 2004-01-01 to calculate the lagged factors.

In [14]:

```
# Shrink the time interval to a valid length.
close_df = close_df[close_df.index >= pd.to_datetime("2004-01-01")]
return_df = return_df[return_df.index >= pd.to_datetime("2004-01-01")]
BM_df = BM_df[BM_df.index >= pd.to_datetime("2004-01-01")]
MV_df = MV_df[MV_df.index >= pd.to_datetime("2004-01-01")]
calender = calender[calender.values >= pd.to_datetime("2004-01-01")]
```

4. Calculate each factors

According to *On Persistence in Mutual Fund Performanc* by **MarK M. Carhart** himself, the model can be interpreted as the following formula:

$$\mathbb{E}[r_{p,t}] - r_f = \alpha + \beta_{RMRF_{p,t}} RMRF_{p,t} + \beta_{SMB_{p,t}} SMB_{p,t} + \beta_{HML_{p,t}} HML_{p,t} + \beta_{UMD_{p,t}} UMD_{p,t}$$

Where r_f is the risk-free interest rate, RMRF is the market risk premium = $r_M - r_f$, and $\mathbb{E}[r_{p,t}]$ is the expected return of portfolio under our assumptions.

Here, we add more factors of momentums, and use the machine learning to reduce the dimensions.

In [15]:

```python
# Daily weighted market values
def GetWeightArray(date: pd.datetime) -> np.array:
    row = MV_df[MV_df.index == date].iloc[0].values
    return row / np.nansum(row)

# Daily market return
def GetMarketReturn(date: pd.datetime) -> float:
    weight = GetWeightArray(date)
    row = return_df[return_df.index == date].iloc[0].values
    return np.nansum([weight[i]*row[i] for i in range(len(row))])


# Daily risk free interest rates
def RF(date: pd.datetime) -> float:
    if date <= pd.to_datetime("2002-08-06"):
        df = deposit_interest_rate

    elif date <= pd.to_datetime("2006-10-07"):
        df = central_bank_bill
    else:
        df = shibor

    if shibor[date <= shibor.iloc[:, 0].values].shape[0] != 0:
        return shibor[date <= shibor.iloc[:, 0].values].iloc[0, 1]
    else:
        raise Exception("Time Interval Exceeded!")


# Daily SMB factor
def GetSMB(date: pd.datetime) -> float:
    row = list(MV_df[MV_df.index == date].iloc[0].values)
    weight = list(GetWeightArray(date))
    returnRow = list(return_df[return_df.index == date].iloc[0].values)

    # filter the stocks
    for i in range(len(returnRow)-1, -1, -1):
        if np.isnan(returnRow[i]) or np.isnan(row[i]):
            weight.pop(i)
            returnRow.pop(i)
            row.pop(i)

    # Determine the stocks to long and short.
    [lower_bound, upper_bound] = np.quantile(row, [tradePercent, 1-tradePercent])
    row, weight, returnRow = np.array(row), np.array(weight), np.array(returnRow)
    return  np.dot(weight[row <= lower_bound], returnRow[row <= lower_bound]) - np.dot(weight|


# Daily HML factor
def GetHML(date: pd.datetime) -> float:
    row = list(BM_df[BM_df.index == date].iloc[0].values)
    weight = list(GetWeightArray(date))
    returnRow = list(return_df[return_df.index == date].iloc[0].values)


    for i in range(len(returnRow)-1, -1, -1):
        if np.isnan(returnRow[i]) or np.isnan(row[i]):
            weight.pop(i)
            returnRow.pop(i)
            row.pop(i)
```

```python

    [lower_bound, upper_bound] = np.quantile(row, [tradePercent, 1-tradePercent])
    row, weight, returnRow = np.array(row), np.array(weight), np.array(returnRow)
    return  np.dot(weight[row >= upper_bound], returnRow[row >= upper_bound]) - np.dot(weight[

```

In [16]:

```python
mom_UMD_df = return_df.copy()
for days in range(2, 13):
    mom_UMD_df = mom_UMD_df + return_df.copy().shift(days, axis = 0)


# Daily UMD factor
def GetUMD(date: pd.datetime) -> float:
    row = list(mom_UMD_df[mom_UMD_df.index == date].iloc[0].values)
    weight = list(GetWeightArray(date))
    returnRow = list(return_df[return_df.index == date].iloc[0].values)

    for i in range(len(returnRow)-1, -1, -1):
        if np.isnan(returnRow[i]) or np.isnan(row[i]):
            weight.pop(i)
            returnRow.pop(i)
            row.pop(i)

    if row == []:
        return np.nan
    else:
        [lower_bound, upper_bound] = np.quantile(row, [tradePercent, 1-tradePercent])
        row, weight, returnRow = np.array(row), np.array(weight), np.array(returnRow)
        return  np.dot(weight[row >= upper_bound], returnRow[row >= upper_bound]) - np.dot(wei
            row <= lower_bound], returnRow[row <= lower_bound])
```

In [17]:

```
# Define some other momentums
mom_12_2_df = return_df.copy()
for days in range(2*30+1, 12*30):
    mom_12_2_df = mom_12_2_df + return_df.copy().shift(days, axis = 0)

# Momentum for the past 12 months lagged 2 month
def mom_12_2(date: pd.datetime) -> float:
    row = list(mom_12_2_df[mom_12_2_df.index == date].iloc[0].values)
    weight = list(GetWeightArray(date))
    returnRow = list(return_df[return_df.index == date].iloc[0].values)

    for i in range(len(returnRow)-1, -1, -1):
        if np.isnan(returnRow[i]) or np.isnan(row[i]):
            weight.pop(i)
            returnRow.pop(i)
            row.pop(i)

    if row == []:
        return np.nan
    else:
        [lower_bound, upper_bound] = np.quantile(row, [tradePercent, 1-tradePercent])
        row, weight, returnRow = np.array(row), np.array(weight), np.array(returnRow)
        return  np.dot(weight[row >= upper_bound], returnRow[row >= upper_bound]) - np.dot(we
            row <= lower_bound], returnRow[row <= lower_bound])



mom_12_7_df = return_df.copy()
for days in range(7*30+1, 12*30):
    mom_12_7_df = mom_12_7_df + return_df.copy().shift(days, axis = 0)

# Momentum for the past 12 months lagged 7 month
def mom_12_7(date: pd.datetime) -> float:
    row = list(mom_12_7_df[mom_12_7_df.index == date].iloc[0].values)
    weight = list(GetWeightArray(date))
    returnRow = list(return_df[return_df.index == date].iloc[0].values)

    for i in range(len(returnRow)-1, -1, -1):
        if np.isnan(returnRow[i]) or np.isnan(row[i]):
            weight.pop(i)
            returnRow.pop(i)
            row.pop(i)

    if row == []:
        return np.nan
    else:
        [lower_bound, upper_bound] = np.quantile(row, [tradePercent, 1-tradePercent])
        row, weight, returnRow = np.array(row), np.array(weight), np.array(returnRow)
        return  np.dot(weight[row >= upper_bound], returnRow[row >= upper_bound]) - np.dot(we
            row <= lower_bound], returnRow[row <= lower_bound])



mom_2_1_df = return_df.copy()
for days in range(30+1, 2*30):
    mom_2_1_df = mom_2_1_df + return_df.copy().shift(days, axis = 0)

# Momentum for the past 2 months lagged 1 month
def mom_2_1(date: pd.datetime) -> float:
```

```python
    row = list(mom_2_1_df[mom_2_1_df.index == date].iloc[0].values)
    weight = list(GetWeightArray(date))
    returnRow = list(return_df[return_df.index == date].iloc[0].values)

    for i in range(len(returnRow)-1, -1, -1):
        if np.isnan(returnRow[i]) or np.isnan(row[i]):
            weight.pop(i)
            returnRow.pop(i)
            row.pop(i)

    if row == []:
        return np.nan
    else:
        [lower_bound, upper_bound] = np.quantile(row, [tradePercent, 1-tradePercent])
        row, weight, returnRow = np.array(row), np.array(weight), np.array(returnRow)
        return  np.dot(weight[row >= upper_bound], returnRow[row >= upper_bound]) - np.dot(we
            row <= lower_bound], returnRow[row <= lower_bound])




mom_20_10_df = return_df.copy()
for days in range(10*30+1, 20*30):
    mom_20_10_df = mom_20_10_df + return_df.copy().shift(days, axis = 0)

# Momentum for the past 20 months lagged 10 month
def mom_20_10(date: pd.datetime) -> float:
    row = list(mom_20_10_df[mom_20_10_df.index == date].iloc[0].values)
    weight = list(GetWeightArray(date))
    returnRow = list(return_df[return_df.index == date].iloc[0].values)

    for i in range(len(returnRow)-1, -1, -1):
        if np.isnan(returnRow[i]) or np.isnan(row[i]):
            weight.pop(i)
            returnRow.pop(i)
            row.pop(i)

    if row == []:
        return np.nan
    else:
        [lower_bound, upper_bound] = np.quantile(row, [tradePercent, 1-tradePercent])
        row, weight, returnRow = np.array(row), np.array(weight), np.array(returnRow)
        return  np.dot(weight[row >= upper_bound], returnRow[row >= upper_bound]) - np.dot(we
            row <= lower_bound], returnRow[row <= lower_bound])



mom_20_13_df = return_df.copy()
for days in range(13*30+1, 20*30):
    mom_20_13_df = mom_20_13_df + return_df.copy().shift(days, axis = 0)

# Momentum for the past 20 months lagged 13 month
def mom_20_13(date: pd.datetime) -> float:
    row = list(mom_20_13_df[mom_20_13_df.index == date].iloc[0].values)
    weight = list(GetWeightArray(date))
    returnRow = list(return_df[return_df.index == date].iloc[0].values)

    for i in range(len(returnRow)-1, -1, -1):
        if np.isnan(returnRow[i]) or np.isnan(row[i]):
            weight.pop(i)
            returnRow.pop(i)
```

```
            row.pop(i)

    if row == []:
        return np.nan
    else:
        [lower_bound, upper_bound] = np.quantile(row, [tradePercent, 1-tradePercent])
        row, weight, returnRow = np.array(row), np.array(weight), np.array(returnRow)
        return  np.dot(weight[row >= upper_bound], returnRow[row >= upper_bound]) - np.dot(we
            row <= lower_bound], returnRow[row <= lower_bound])
```

In [18]:

```
# Daily monmemtums
# Define some other momentums
momd_10_5_df = return_df.copy()
for days in range(5, 10):
    momd_10_5_df = momd_10_5_df + return_df.copy().shift(days, axis = 0)

# Momentum for the past 10 days lagged 5 days
def momd_10_5(date: pd.datetime) -> float:
    row = list(momd_10_5_df[momd_10_5_df.index == date].iloc[0].values)
    weight = list(GetWeightArray(date))
    returnRow = list(return_df[return_df.index == date].iloc[0].values)

    for i in range(len(returnRow)-1, -1, -1):
        if np.isnan(returnRow[i]) or np.isnan(row[i]):
            weight.pop(i)
            returnRow.pop(i)
            row.pop(i)

    if row == []:
        return np.nan
    else:
        [lower_bound, upper_bound] = np.quantile(row, [tradePercent, 1-tradePercent])
        row, weight, returnRow = np.array(row), np.array(weight), np.array(returnRow)
        return  np.dot(weight[row >= upper_bound], returnRow[row >= upper_bound]) - np.dot(we
            row <= lower_bound], returnRow[row <= lower_bound])



momd_25_5_df = return_df.copy()
for days in range(5, 25):
    momd_25_5_df = momd_25_5_df + return_df.copy().shift(days, axis = 0)

# Momentum for the past 25 days lagged 5 days
def momd_25_5(date: pd.datetime) -> float:
    row = list(momd_25_5_df[momd_25_5_df.index == date].iloc[0].values)
    weight = list(GetWeightArray(date))
    returnRow = list(return_df[return_df.index == date].iloc[0].values)

    for i in range(len(returnRow)-1, -1, -1):
        if np.isnan(returnRow[i]) or np.isnan(row[i]):
            weight.pop(i)
            returnRow.pop(i)
            row.pop(i)

    if row == []:
        return np.nan
    else:
        [lower_bound, upper_bound] = np.quantile(row, [tradePercent, 1-tradePercent])
        row, weight, returnRow = np.array(row), np.array(weight), np.array(returnRow)
        return  np.dot(weight[row >= upper_bound], returnRow[row >= upper_bound]) - np.dot(we
            row <= lower_bound], returnRow[row <= lower_bound])



momd_7_2_df = return_df.copy()
for days in range(2, 7):
    momd_7_2_df = momd_7_2_df + return_df.copy().shift(days, axis = 0)

# Momentum for the past 7 days lagged 2 days
```

```python
def momd_7_2(date: pd.datetime) -> float:
    row = list(momd_7_2_df[momd_7_2_df.index == date].iloc[0].values)
    weight = list(GetWeightArray(date))
    returnRow = list(return_df[return_df.index == date].iloc[0].values)

    for i in range(len(returnRow)-1, -1, -1):
        if np.isnan(returnRow[i]) or np.isnan(row[i]):
            weight.pop(i)
            returnRow.pop(i)
            row.pop(i)

    if row == []:
        return np.nan
    else:
        [lower_bound, upper_bound] = np.quantile(row, [tradePercent, 1-tradePercent])
        row, weight, returnRow = np.array(row), np.array(weight), np.array(returnRow)
        return  np.dot(weight[row >= upper_bound], returnRow[row >= upper_bound]) - np.dot(we
            row <= lower_bound], returnRow[row <= lower_bound])



momd_40_10_df = return_df.copy()
for days in range(10, 40):
    momd_40_10_df = momd_40_10_df + return_df.copy().shift(days, axis = 0)

# Momentum for the past 40 days lagged 10 days
def momd_40_10(date: pd.datetime) -> float:
    row = list(momd_40_10_df[momd_40_10_df.index == date].iloc[0].values)
    weight = list(GetWeightArray(date))
    returnRow = list(return_df[return_df.index == date].iloc[0].values)

    for i in range(len(returnRow)-1, -1, -1):
        if np.isnan(returnRow[i]) or np.isnan(row[i]):
            weight.pop(i)
            returnRow.pop(i)
            row.pop(i)

    if row == []:
        return np.nan
    else:
        [lower_bound, upper_bound] = np.quantile(row, [tradePercent, 1-tradePercent])
        row, weight, returnRow = np.array(row), np.array(weight), np.array(returnRow)
        return  np.dot(weight[row >= upper_bound], returnRow[row >= upper_bound]) - np.dot(we
            row <= lower_bound], returnRow[row <= lower_bound])



momd_30_20_df = return_df.copy()
for days in range(20, 30):
    momd_30_20_df = momd_30_20_df + return_df.copy().shift(days, axis = 0)

# Momentum for the past 30 days lagged 20 days
def momd_30_20(date: pd.datetime) -> float:
    row = list(momd_30_20_df[momd_30_20_df.index == date].iloc[0].values)
    weight = list(GetWeightArray(date))
    returnRow = list(return_df[return_df.index == date].iloc[0].values)

    for i in range(len(returnRow)-1, -1, -1):
        if np.isnan(returnRow[i]) or np.isnan(row[i]):
            weight.pop(i)
            returnRow.pop(i)
```

```
            row.pop(i)

    if row == []:
        return np.nan
    else:
        [lower_bound, upper_bound] = np.quantile(row, [tradePercent, 1-tradePercent])
        row, weight, returnRow = np.array(row), np.array(weight), np.array(returnRow)
        return  np.dot(weight[row >= upper_bound], returnRow[row >= upper_bound]) - np.dot(we
            row <= lower_bound], returnRow[row <= lower_bound])
```

4.2. Calculate the result for four-factor model

In [19]:

```
multiFactor = pd.DataFrame({"RF": np.nan, "MKT": np.nan, "RMRF": np.nan , "SMB": np.nan,
                            "HML": np.nan, "UMD": np.nan, "mom_12_2":np.nan, "mom_12_7": np.nan
                            "mom_2_1": np.nan, "mom_20_10": np.nan, "mom_20_13": np.nan,
                            "momd_10_5": np.nan, "momd_25_5": np.nan, "momd_7_2": np.nan,
                            "momd_40_10": np.nan, "momd_30_20": np.nan},
                           index = pd.to_datetime(calender.values))

multiFactor["RF"] = np.array(map(RF, multiFactor.index))
multiFactor["MKT"] = np.array(map(GetMarketReturn, multiFactor.index))
multiFactor["RMRF"] = multiFactor["MKT"] - multiFactor["RF"]
multiFactor["SMB"] = np.array(map(GetSMB, multiFactor.index))
multiFactor["HML"] = np.array(map(GetHML, multiFactor.index))
multiFactor["UMD"] = np.array(map(GetUMD, multiFactor.index))
multiFactor["mom_12_2"] = np.array(map(mom_12_2, multiFactor.index))
del mom_12_2_df
multiFactor["mom_12_7"] = np.array(map(mom_12_7, multiFactor.index))
del mom_12_7_df
multiFactor["mom_20_10"] = np.array(map(mom_20_10, multiFactor.index))
del mom_20_10_df
multiFactor["mom_2_1"] = np.array(map(mom_2_1, multiFactor.index))
del mom_2_1_df
multiFactor["mom_20_13"] = np.array(map(mom_20_13, multiFactor.index))
del mom_20_13_df
multiFactor["momd_10_5"] = np.array(map(momd_10_5, multiFactor.index))
del momd_10_5_df
multiFactor["momd_25_5"] = np.array(map(momd_25_5, multiFactor.index))
del momd_25_5_df
multiFactor["momd_7_2"] = np.array(map(momd_7_2, multiFactor.index))
del momd_7_2_df
multiFactor["momd_40_10"] = np.array(map(momd_40_10, multiFactor.index))
del momd_40_10_df
multiFactor["momd_30_20"] = np.array(map(momd_30_20, multiFactor.index))
del momd_30_20_df

multiFactor.fillna(method="bfill", inplace=True)
return_df = return_df.loc[multiFactor.index]
return_df.drop(columns = return_df.columns[return_df.iloc[0:3, :].sum() == 0], inplace=True)
multiFactor.to_csv("C:\\Users\\tianj\\Project 1\\data\\multifactor.csv", index=True, header=Tr
```

In [20]:

```
scaled_data = pd.DataFrame(StandardScaler().fit_transform(multiFactor))
scaled_data.columns = multiFactor.columns
scaled_data.index = multiFactor.index
scaled_data
```

Out[20]:

	RF	MKT	RMRF	SMB	HML	UMD	mom_12_2	mom_12_7
2004-01-02	-0.684437	1.452312	1.456804	-1.795572	0.058230	-0.252906	-0.122065	-0.18933
2004-01-05	-0.684437	3.629775	3.633808	-4.147158	-0.309253	-0.252906	-0.122065	-0.18933
2004-01-06	-0.684437	0.493796	0.498489	-0.263054	-0.228629	-0.252906	-0.122065	-0.18933
2004-01-07	-0.684437	0.286796	0.291533	-0.143986	-0.233113	-0.252906	-0.122065	-0.18933
2004-01-08	-0.684437	0.582649	0.587323	-0.312088	-0.086065	-0.252906	-0.122065	-0.18933
...	...	...	...	...	...	...	...	..
2021-12-27	-0.831960	-0.087997	-0.082148	0.180072	0.076469	-0.100582	0.061886	0.18687
2021-12-28	-0.831960	0.276391	0.282163	-0.193698	-0.190914	-0.936703	3.480145	1.81419
2021-12-29	-0.831960	-0.756216	-0.750226	0.596629	0.819726	-0.280441	-0.712702	-0.85269
2021-12-30	-0.831960	0.281060	0.286831	-0.113176	-0.511690	-0.081638	-0.145113	-0.93335
2021-12-31	-0.831960	0.128113	0.133917	0.062335	0.248269	0.164809	1.761075	0.89860

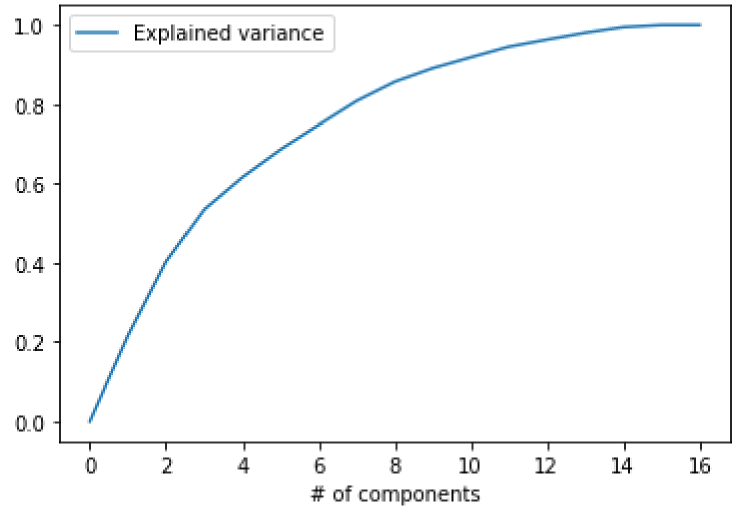
4375 rows × 16 columns

In [21]:

```
explained_var = []
for num in range(multiFactor.shape[1] + 1):
    pca = PCA(num)
    pca.fit(scaled_data, return_df)
    explained_var.append([num, sum(pca.explained_variance_ratio_)])

pd.DataFrame(explained_var, columns=["# of components", "Explained variance"]).set_index(
    "# of components").plot()
```

Out[21]:

<AxesSubplot:xlabel='# of components'>



In [22]:

```
pca = PCA(n_components=7)
pca.fit(scaled_data, return_df)
print(f"Variance explained: {pca.explained_variance_ratio_}")
PCA_result = pd.DataFrame(pca.fit_transform(scaled_data))
PCA_result.columns = ["f1", "f2", "f3", "f4", "f5", "f6", "f7"]
PCA_result.index = multiFactor.index
PCA_result
```

```
Variance explained: [0.21573814 0.18712418 0.13201281 0.08143315 0.06973252 0.061925
34
 0.06052519]
```

Out[22]:

	f1	f2	f3	f4	f5	f6	f7
2004-01-02	-1.684379	2.597687	-0.761652	-1.325078	-0.056674	0.694733	-0.088505
2004-01-05	-2.530394	6.219111	-1.223979	-0.624407	-0.197871	0.795987	0.520827
2004-01-06	-1.232375	0.723412	-0.420215	-1.676986	-0.054431	0.724496	0.057119
2004-01-07	-1.162282	0.433492	-0.381193	-1.733784	-0.044792	0.720615	0.036928
2004-01-08	-1.268939	0.851488	-0.462025	-1.653510	-0.041364	0.703699	-0.065415
...	...	...	...	...	...	...	...
2021-12-27	0.054105	-0.115739	0.308105	-0.141849	0.128801	0.725702	-0.223780
2021-12-28	-0.247953	0.878797	3.547994	0.831103	-1.923314	0.980499	-0.843057
2021-12-29	-0.272106	-1.177744	-1.364762	-1.377535	0.498332	0.693610	-0.777565
2021-12-30	0.534601	0.893904	1.765952	-0.041164	2.592242	0.359462	0.515534
2021-12-31	0.490775	0.624902	1.511794	-0.353425	-0.881954	0.711772	-0.717901

4375 rows × 7 columns

Construct LSTM model for stock data

In [23]:

```
df = pd.DataFrame(return_df.sum(axis=1))
df = pd.DataFrame(StandardScaler().fit_transform(df))
df.columns = ["return"]
df["Date"] = multiFactor.index
df = df.rename(columns={"index": "Date"})
```

In [24]:

```
# Use CPU to run the model
os.environ["CUDA_VISIBLE_DEVICES"] = "-1"
```

In [25]:

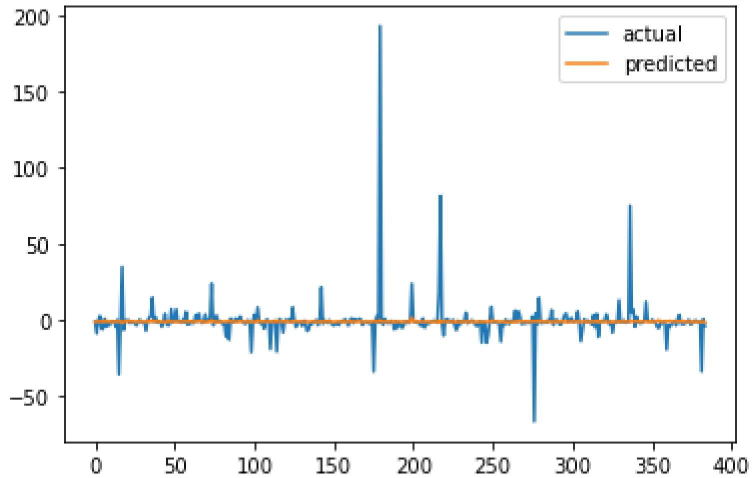
```
def build_model(inputs, output_size, neurons, activ_func="linear",
                dropout=0.10, loss="mae", optimizer="adam"):

    model = Sequential()

    model.add(LSTM(neurons, input_shape=(inputs.shape[1], inputs.shape[2])))
    model.add(Dropout(dropout))
    model.add(Dense(units=output_size))
    model.add(Activation(activ_func))

    model.compile(loss=loss, optimizer=optimizer)
    return model
```

In [26]:

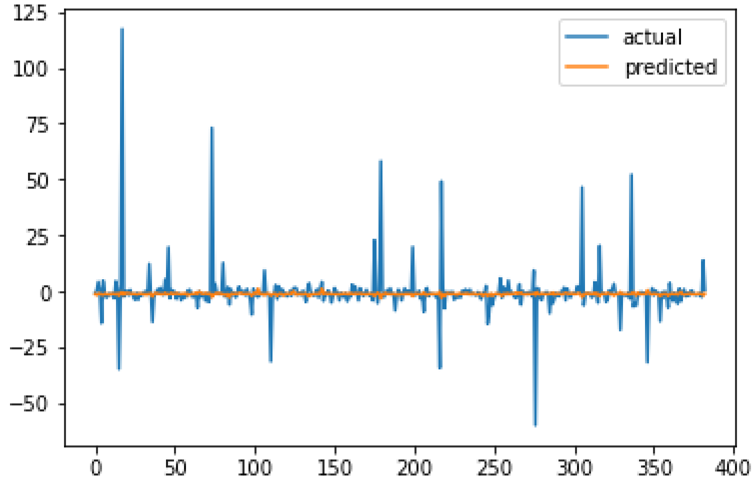
```python
window_len_lst = list(range(5, 20))
window_dic = {}

for window_len in window_len_lst:
    split_date = "2020-06-01"
    print("split_date:",split_date)

    # Split the training and test set
    training_set, test_set = df[df["Date"] < split_date], df[df["Date"] >= split_date]
    training_set = training_set.drop(["Date"], 1)
    test_set = test_set.drop(["Date"], 1)

    # Create windows for training
    LSTM_training_inputs = []
    for i in range(len(training_set)-window_len):
        temp_set = training_set[i:(i+window_len)].copy()

        for col in list(temp_set):
            temp_set[col] = temp_set[col]/temp_set[col].iloc[0] - 1

        LSTM_training_inputs.append(temp_set)
    LSTM_training_inputs
    LSTM_training_outputs = (training_set["return"][window_len:].values/training_set[
        "return"][:-window_len].values)-1

    LSTM_training_inputs = [np.array(LSTM_training_input) for LSTM_training_input in LSTM_trai
    LSTM_training_inputs = np.array(LSTM_training_inputs)

    # Create windows for testing
    LSTM_test_inputs = []
    for i in range(len(test_set)-window_len):
        temp_set = test_set[i:(i+window_len)].copy()

        for col in list(temp_set):
            temp_set[col] = temp_set[col]/temp_set[col].iloc[0] - 1

        LSTM_test_inputs.append(temp_set)
    LSTM_test_outputs = (test_set["return"][window_len:].values/test_set["return"][:-window_le

    LSTM_test_inputs = [np.array(LSTM_test_inputs) for LSTM_test_inputs in LSTM_test_inputs]
    LSTM_test_inputs = np.array(LSTM_test_inputs)

    # initialise model architecture
    nn_model = build_model(LSTM_training_inputs, output_size=1, neurons = 32)
    # model output is next price normalised to 10th previous closing price train model on data
    # note: eth_history contains information on the training error per epoch
    nn_history = nn_model.fit(LSTM_training_inputs, LSTM_training_outputs,
                              epochs=5, batch_size=1, verbose=2, shuffle=True)
    plt.plot(LSTM_test_outputs, label = "actual")
    plt.plot(nn_model.predict(LSTM_test_inputs), label = "predicted")
    plt.legend()
    plt.show()
    MAE = mean_absolute_error(LSTM_test_outputs, nn_model.predict(LSTM_test_inputs))
    window_dic[window_len] = MAE
window_result = pd.DataFrame(window_dic.values(), window_dic.keys()).rename(columns={0: "MAE"})
```

```
split_date: 2020-06-01
Epoch 1/5
```

```
3981/3981 - 4s - loss: 16.1409 - 4s/epoch - 1ms/step
Epoch 2/5
3981/3981 - 3s - loss: 16.1233 - 3s/epoch - 878us/step
Epoch 3/5
3981/3981 - 4s - loss: 16.1218 - 4s/epoch - 885us/step
Epoch 4/5
3981/3981 - 4s - loss: 16.1193 - 4s/epoch - 880us/step
Epoch 5/5
3981/3981 - 4s - loss: 16.1145 - 4s/epoch - 885us/step
```

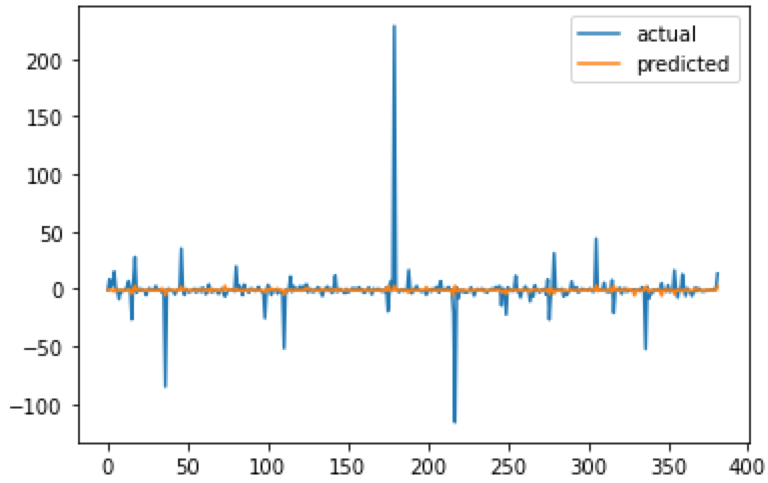



```
split_date: 2020-06-01
Epoch 1/5
3980/3980 - 5s - loss: 10.9338 - 5s/epoch - 1ms/step
Epoch 2/5
3980/3980 - 4s - loss: 10.9197 - 4s/epoch - 957us/step
Epoch 3/5
3980/3980 - 4s - loss: 10.9161 - 4s/epoch - 950us/step
Epoch 4/5
3980/3980 - 4s - loss: 10.9198 - 4s/epoch - 941us/step
Epoch 5/5
3980/3980 - 4s - loss: 10.9115 - 4s/epoch - 947us/step
```

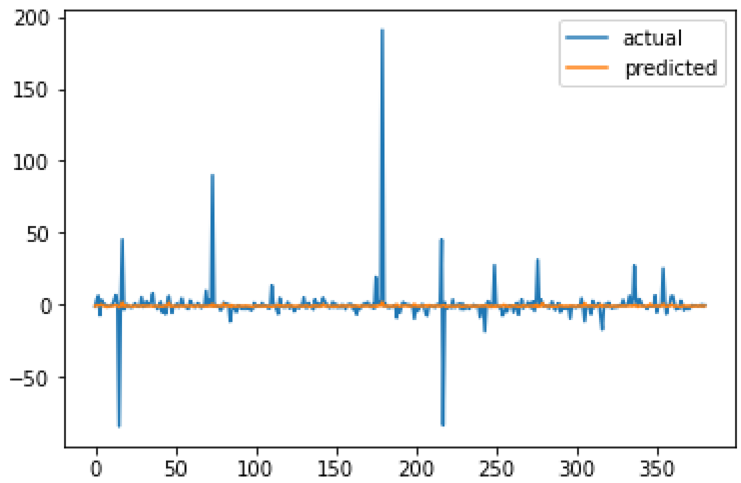



```
split_date: 2020-06-01
Epoch 1/5
3979/3979 - 5s - loss: 11.3503 - 5s/epoch - 1ms/step
Epoch 2/5
3979/3979 - 4s - loss: 11.3332 - 4s/epoch - 1ms/step
Epoch 3/5
3979/3979 - 4s - loss: 11.3209 - 4s/epoch - 1ms/step
Epoch 4/5
3979/3979 - 4s - loss: 11.3183 - 4s/epoch - 1ms/step
```

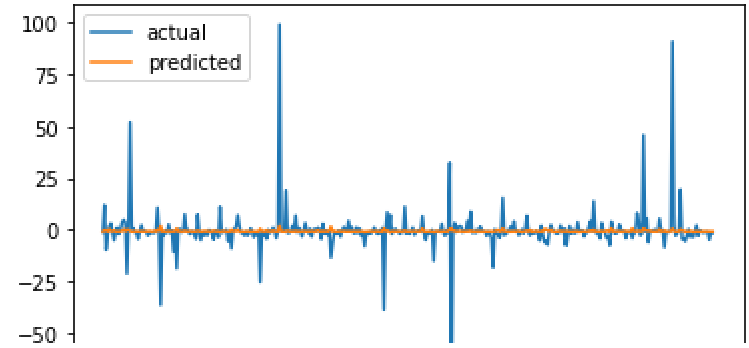
```
Epoch 5/5
3979/3979 - 4s - loss: 11.3090 - 4s/epoch - 1ms/step
```



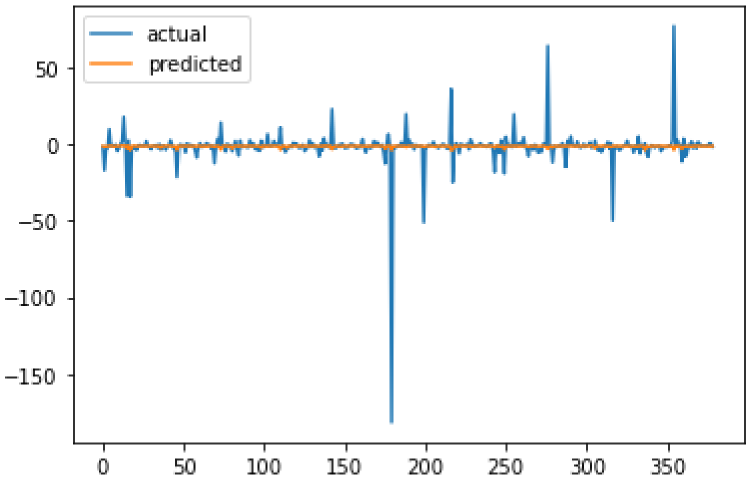

```
split_date: 2020-06-01
Epoch 1/5
3978/3978 - 5s - loss: 8.4297 - 5s/epoch - 1ms/step
Epoch 2/5
3978/3978 - 4s - loss: 8.4147 - 4s/epoch - 1ms/step
Epoch 3/5
3978/3978 - 4s - loss: 8.4121 - 4s/epoch - 1ms/step
Epoch 4/5
3978/3978 - 4s - loss: 8.4074 - 4s/epoch - 1ms/step
Epoch 5/5
3978/3978 - 4s - loss: 8.4053 - 4s/epoch - 1ms/step
```




```
split_date: 2020-06-01
Epoch 1/5
3977/3977 - 5s - loss: 10.3806 - 5s/epoch - 1ms/step
Epoch 2/5
3977/3977 - 5s - loss: 10.3703 - 5s/epoch - 1ms/step
Epoch 3/5
3977/3977 - 5s - loss: 10.3744 - 5s/epoch - 1ms/step
Epoch 4/5
3977/3977 - 5s - loss: 10.3700 - 5s/epoch - 1ms/step
Epoch 5/5
3977/3977 - 5s - loss: 10.3646 - 5s/epoch - 1ms/step
```

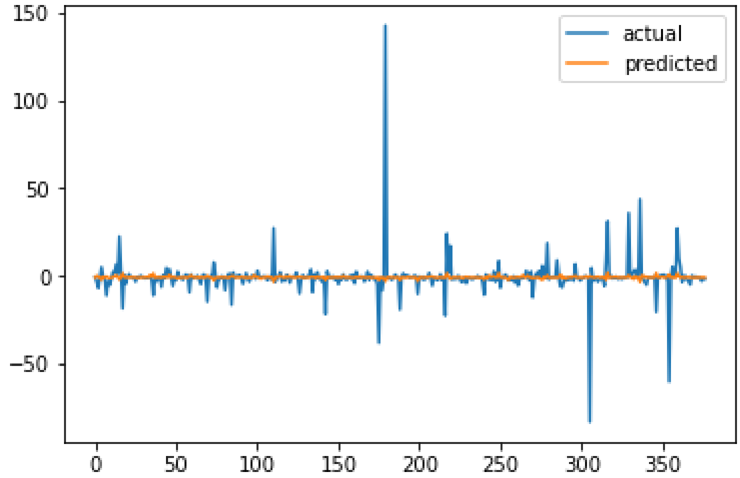



```
split_date: 2020-06-01
Epoch 1/5
3976/3976 - 6s - loss: 13.1201 - 6s/epoch - 1ms/step
Epoch 2/5
3976/3976 - 5s - loss: 13.1094 - 5s/epoch - 1ms/step
Epoch 3/5
3976/3976 - 5s - loss: 13.1019 - 5s/epoch - 1ms/step
Epoch 4/5
3976/3976 - 5s - loss: 13.1003 - 5s/epoch - 1ms/step
Epoch 5/5
3976/3976 - 5s - loss: 13.0956 - 5s/epoch - 1ms/step
```

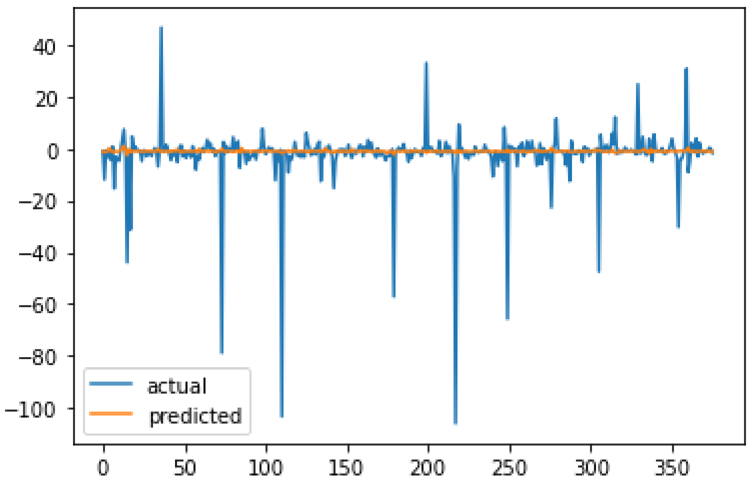



```
split_date: 2020-06-01
Epoch 1/5
3975/3975 - 6s - loss: 6.5981 - 6s/epoch - 2ms/step
Epoch 2/5
3975/3975 - 5s - loss: 6.5899 - 5s/epoch - 1ms/step
Epoch 3/5
3975/3975 - 5s - loss: 6.5839 - 5s/epoch - 1ms/step
Epoch 4/5
3975/3975 - 5s - loss: 6.5900 - 5s/epoch - 1ms/step
Epoch 5/5
3975/3975 - 5s - loss: 6.5827 - 5s/epoch - 1ms/step
```

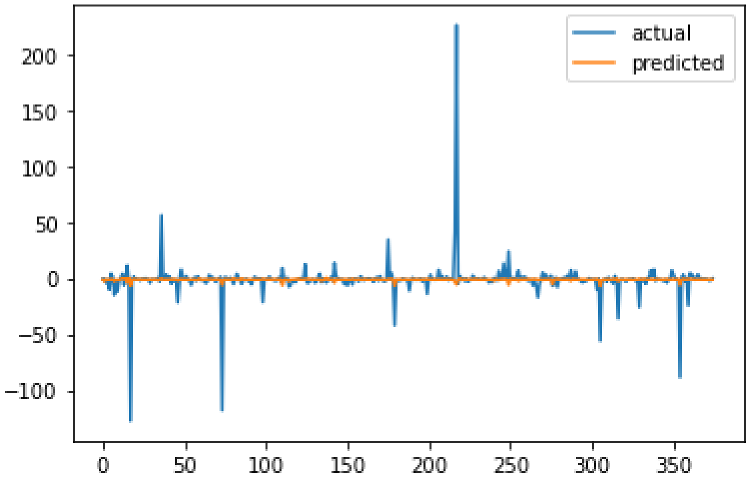

```
split_date: 2020-06-01
Epoch 1/5
3974/3974 - 6s - loss: 13.4643 - 6s/epoch - 2ms/step
Epoch 2/5
3974/3974 - 6s - loss: 13.4543 - 6s/epoch - 1ms/step
Epoch 3/5
3974/3974 - 6s - loss: 13.4521 - 6s/epoch - 1ms/step
Epoch 4/5
3974/3974 - 6s - loss: 13.4488 - 6s/epoch - 1ms/step
Epoch 5/5
3974/3974 - 6s - loss: 13.4387 - 6s/epoch - 1ms/step
```



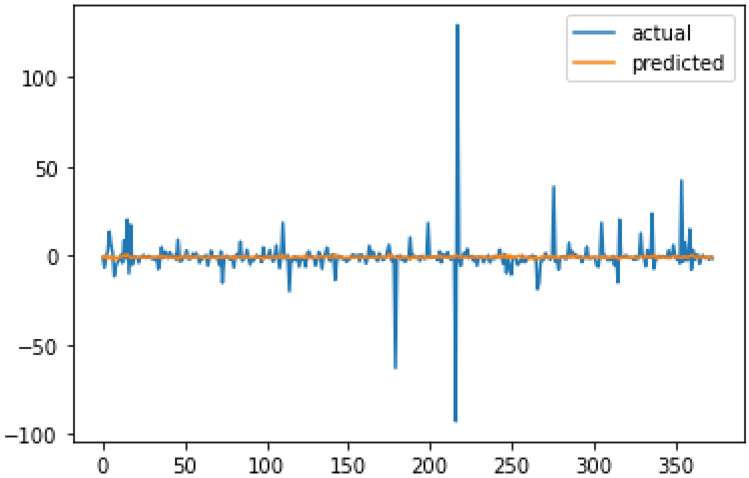

```
split_date: 2020-06-01
Epoch 1/5
3973/3973 - 7s - loss: 7.3606 - 7s/epoch - 2ms/step
Epoch 2/5
3973/3973 - 6s - loss: 7.3506 - 6s/epoch - 1ms/step
Epoch 3/5
3973/3973 - 6s - loss: 7.3490 - 6s/epoch - 1ms/step
Epoch 4/5
3973/3973 - 6s - loss: 7.3443 - 6s/epoch - 1ms/step
Epoch 5/5
3973/3973 - 6s - loss: 7.3404 - 6s/epoch - 1ms/step
```



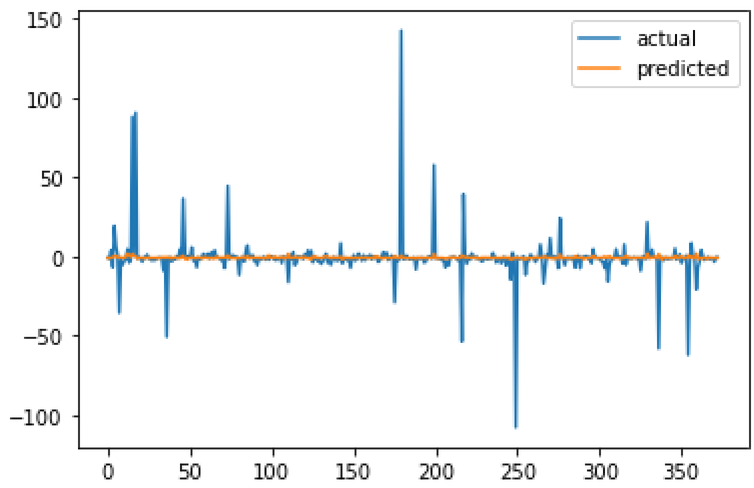
```
split_date: 2020-06-01
Epoch 1/5
3972/3972 - 7s - loss: 13.8478 - 7s/epoch - 2ms/step
Epoch 2/5
3972/3972 - 6s - loss: 13.8347 - 6s/epoch - 2ms/step
Epoch 3/5
3972/3972 - 6s - loss: 13.8281 - 6s/epoch - 2ms/step
Epoch 4/5
3972/3972 - 6s - loss: 13.8200 - 6s/epoch - 2ms/step
Epoch 5/5
3972/3972 - 6s - loss: 13.8070 - 6s/epoch - 2ms/step
```



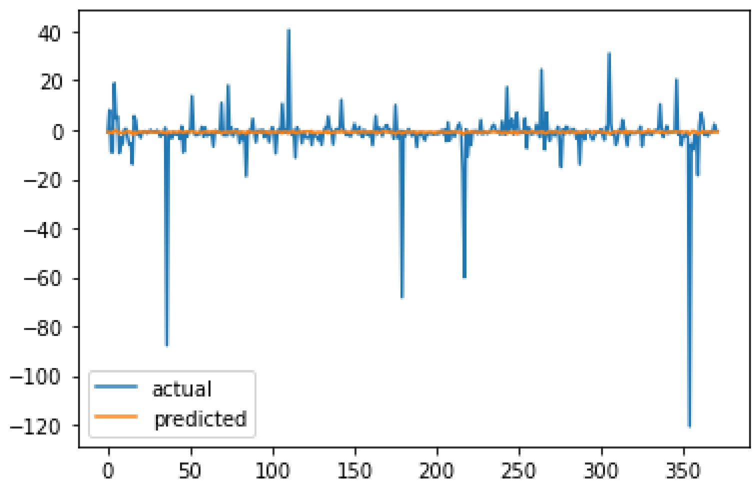

```
split_date: 2020-06-01
Epoch 1/5
3971/3971 - 7s - loss: 12.2154 - 7s/epoch - 2ms/step
Epoch 2/5
3971/3971 - 7s - loss: 12.2017 - 7s/epoch - 2ms/step
Epoch 3/5
3971/3971 - 8s - loss: 12.1963 - 8s/epoch - 2ms/step
Epoch 4/5
3971/3971 - 8s - loss: 12.1942 - 8s/epoch - 2ms/step
Epoch 5/5
3971/3971 - 8s - loss: 12.1954 - 8s/epoch - 2ms/step
```



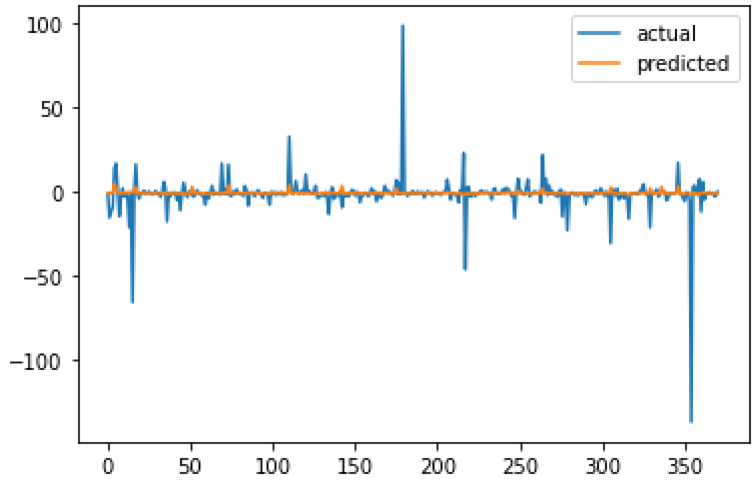
```
split_date: 2020-06-01
Epoch 1/5
3970/3970 - 9s - loss: 8.8355 - 9s/epoch - 2ms/step
Epoch 2/5
3970/3970 - 7s - loss: 8.8268 - 7s/epoch - 2ms/step
Epoch 3/5
3970/3970 - 7s - loss: 8.8132 - 7s/epoch - 2ms/step
Epoch 4/5
3970/3970 - 7s - loss: 8.8152 - 7s/epoch - 2ms/step
Epoch 5/5
3970/3970 - 7s - loss: 8.8095 - 7s/epoch - 2ms/step
```



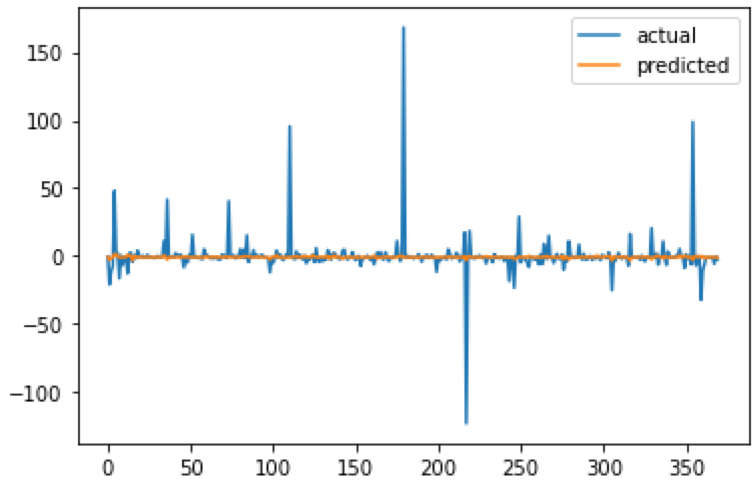

```
split_date: 2020-06-01
Epoch 1/5
3969/3969 - 8s - loss: 9.9439 - 8s/epoch - 2ms/step
Epoch 2/5
3969/3969 - 8s - loss: 9.9345 - 8s/epoch - 2ms/step
Epoch 3/5
3969/3969 - 8s - loss: 9.9254 - 8s/epoch - 2ms/step
Epoch 4/5
3969/3969 - 8s - loss: 9.9247 - 8s/epoch - 2ms/step
Epoch 5/5
3969/3969 - 9s - loss: 9.9165 - 9s/epoch - 2ms/step
```



```
split_date: 2020-06-01
Epoch 1/5
3968/3968 - 8s - loss: 13.5348 - 8s/epoch - 2ms/step
Epoch 2/5
3968/3968 - 8s - loss: 13.5206 - 8s/epoch - 2ms/step
Epoch 3/5
3968/3968 - 9s - loss: 13.5128 - 9s/epoch - 2ms/step
Epoch 4/5
3968/3968 - 9s - loss: 13.5075 - 9s/epoch - 2ms/step
Epoch 5/5
3968/3968 - 8s - loss: 13.4979 - 8s/epoch - 2ms/step
```




```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 10s - loss: 9.4345 - 10s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 9s - loss: 9.4270 - 9s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4186 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 9s - loss: 9.4124 - 9s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 9s - loss: 9.4038 - 9s/epoch - 2ms/step
```



In [37]:

```
window_result[window_result == window_result.min()].dropna()
```

Out[37]:

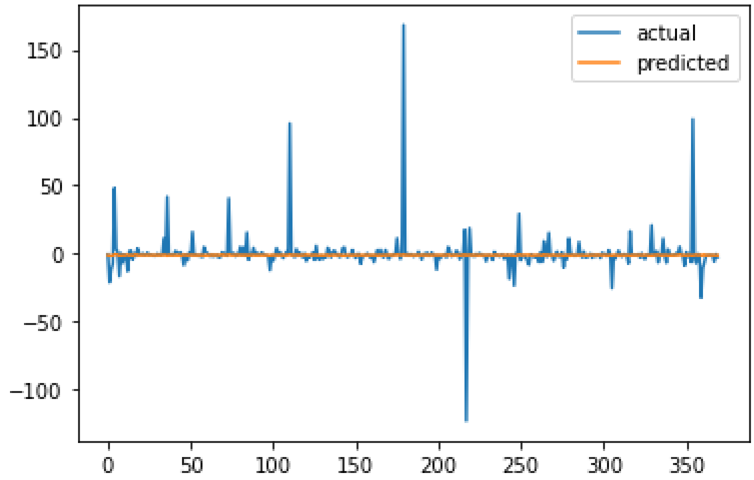
	MAE
11	3.386592

In [27]:

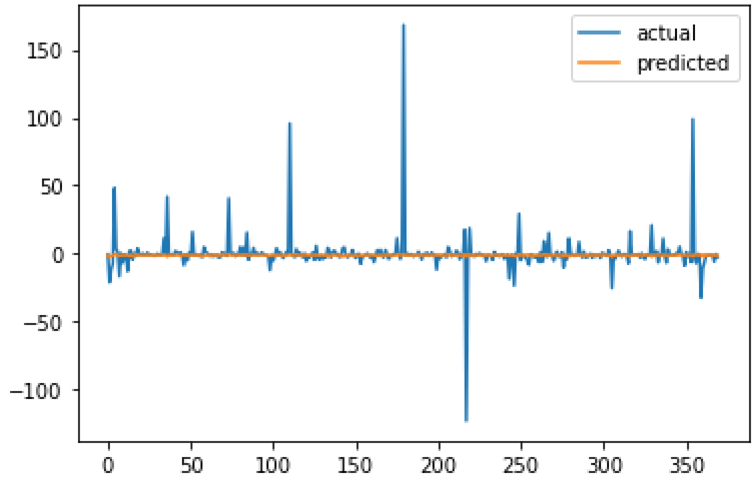
```
neurons_lst = np.arange(5, 50, 5)
neurons_dic = {}

for neurons in neurons_lst:
    split_date = "2020-06-01"
    print("split_date:",split_date)

    # Split the training and test set
    training_set, test_set = df[df["Date"] < split_date], df[df["Date"] >= split_date]
    training_set = training_set.drop(["Date"], 1)
    test_set = test_set.drop(["Date"], 1)

    # Create windows for training
    LSTM_training_inputs = []
    for i in range(len(training_set)-window_len):
        temp_set = training_set[i:(i+window_len)].copy()

        for col in list(temp_set):
            temp_set[col] = temp_set[col]/temp_set[col].iloc[0] - 1

        LSTM_training_inputs.append(temp_set)
    LSTM_training_inputs
    LSTM_training_outputs = (training_set["return"][window_len:].values/training_set[
        "return"][:-window_len].values)-1

    LSTM_training_inputs = [np.array(LSTM_training_input) for LSTM_training_input in LSTM_trai
    LSTM_training_inputs = np.array(LSTM_training_inputs)

    # Create windows for testing
    LSTM_test_inputs = []
    for i in range(len(test_set)-window_len):
        temp_set = test_set[i:(i+window_len)].copy()

        for col in list(temp_set):
            temp_set[col] = temp_set[col]/temp_set[col].iloc[0] - 1

        LSTM_test_inputs.append(temp_set)
    LSTM_test_outputs = (test_set["return"][window_len:].values/test_set["return"][:-window_len

    LSTM_test_inputs = [np.array(LSTM_test_inputs) for LSTM_test_inputs in LSTM_test_inputs]
    LSTM_test_inputs = np.array(LSTM_test_inputs)

    # initialise model architecture
    nn_model = build_model(LSTM_training_inputs, output_size=1, neurons = neurons)
    # model output is next price normalised to 10th previous closing price train model on data
    # note: eth_history contains information on the training error per epoch
    nn_history = nn_model.fit(LSTM_training_inputs, LSTM_training_outputs,
                              epochs=5, batch_size=1, verbose=2, shuffle=True)
    plt.plot(LSTM_test_outputs, label = "actual")
    plt.plot(nn_model.predict(LSTM_test_inputs), label = "predicted")
    plt.legend()
    plt.show()
    MAE = mean_absolute_error(LSTM_test_outputs, nn_model.predict(LSTM_test_inputs))
    neurons_dic[neurons] = MAE
neurons_result = pd.DataFrame(neurons_dic.values(), neurons_dic.keys()).rename(columns={0: "MAE
```

```
split_date: 2020-06-01
Epoch 1/5
```

```
3967/3967 - 9s - loss: 9.4452 - 9s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4310 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4294 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 9s - loss: 9.4245 - 9s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4290 - 8s/epoch - 2ms/step
```

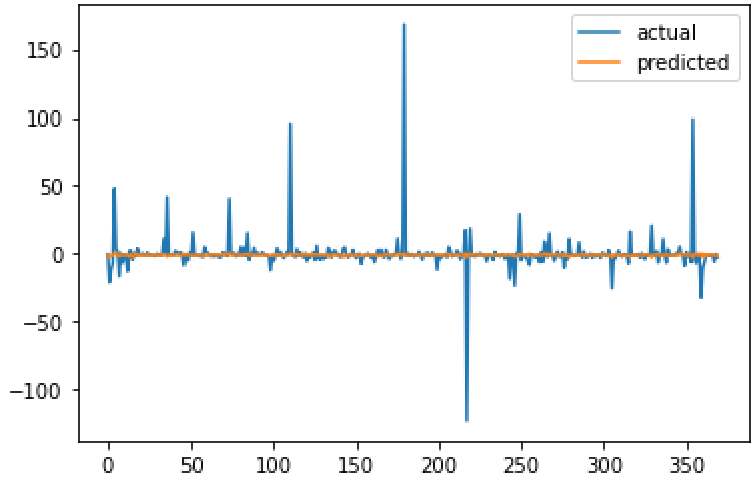



```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 9s - loss: 9.4540 - 9s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 10s - loss: 9.4354 - 10s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 9s - loss: 9.4277 - 9s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 9s - loss: 9.4215 - 9s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 9s - loss: 9.4251 - 9s/epoch - 2ms/step
```

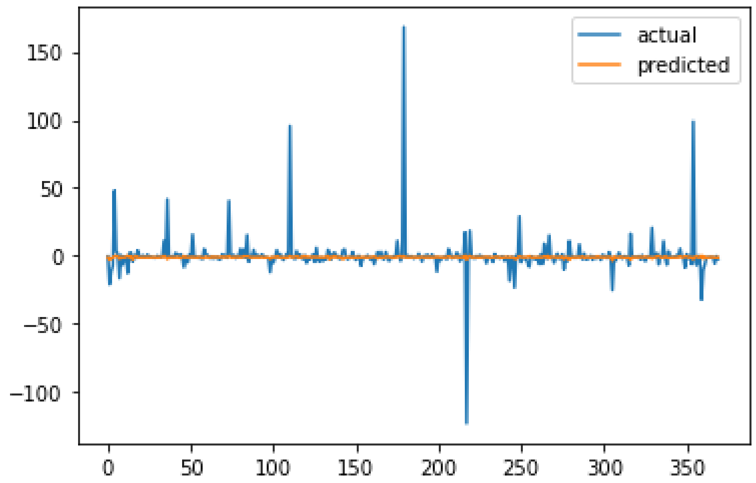



```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 8s - loss: 9.4346 - 8s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 7s - loss: 9.4237 - 7s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4245 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4188 - 8s/epoch - 2ms/step
```

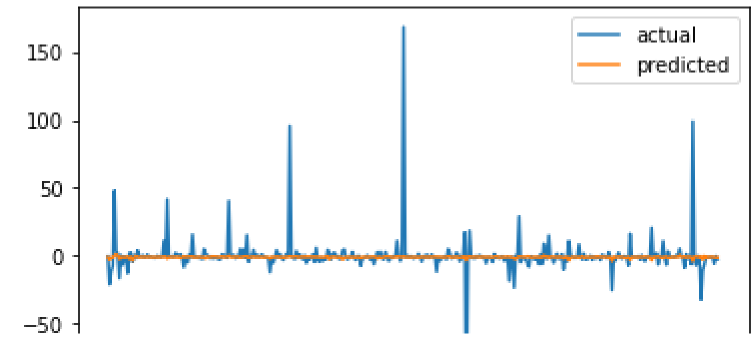
```
Epoch 5/5
3967/3967 - 8s - loss: 9.4150 - 8s/epoch - 2ms/step
```



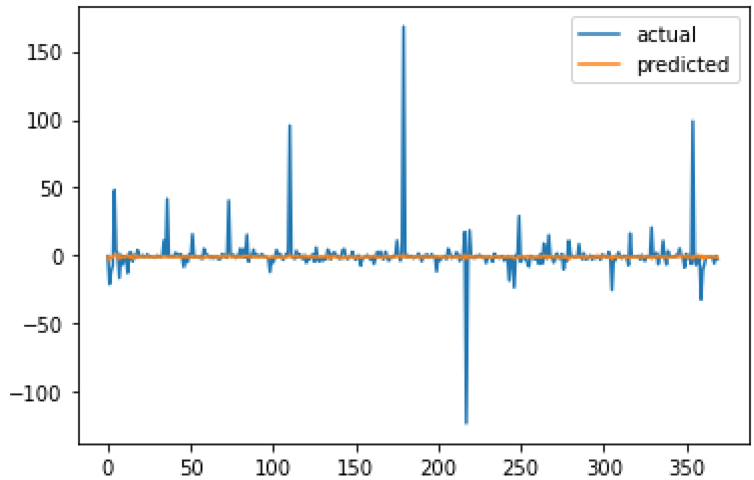

```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 8s - loss: 9.4382 - 8s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 7s - loss: 9.4278 - 7s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4237 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4173 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4122 - 8s/epoch - 2ms/step
```



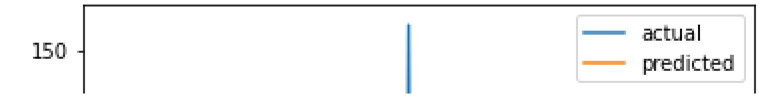

```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 10s - loss: 9.4340 - 10s/epoch - 3ms/step
Epoch 2/5
3967/3967 - 9s - loss: 9.4288 - 9s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4206 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4202 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4160 - 8s/epoch - 2ms/step
```



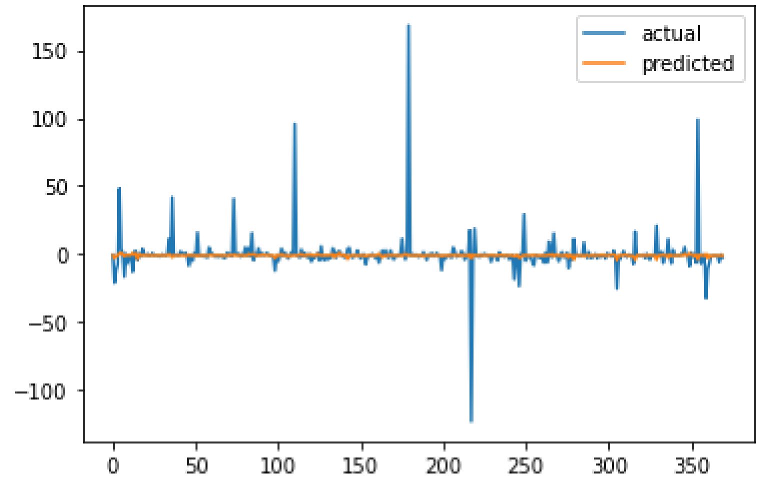

```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 9s - loss: 9.4387 - 9s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4241 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4256 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4193 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4159 - 8s/epoch - 2ms/step
```



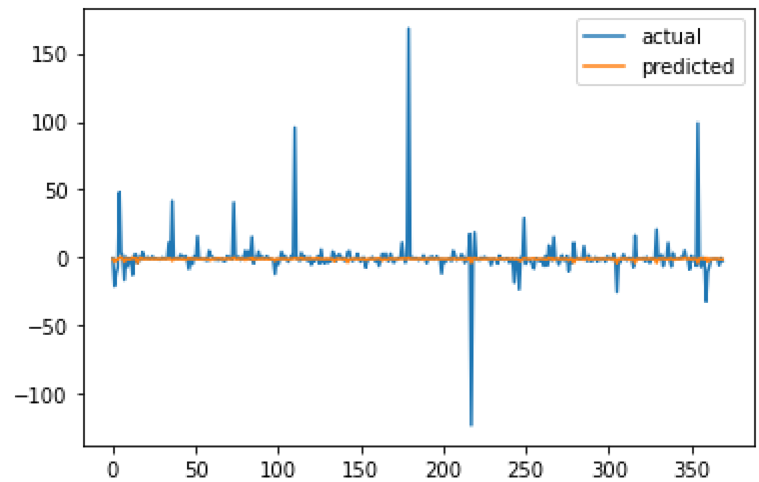

```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 9s - loss: 9.4343 - 9s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4286 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4229 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4123 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4097 - 8s/epoch - 2ms/step
```




```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 9s - loss: 9.4348 - 9s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4228 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4184 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4070 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4073 - 8s/epoch - 2ms/step
```




```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 9s - loss: 9.4406 - 9s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4258 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4257 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4168 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4194 - 8s/epoch - 2ms/step
```



In [40]:

```
neurons_result[neurons_result == neurons_result.min()].dropna()
```

Out[40]:

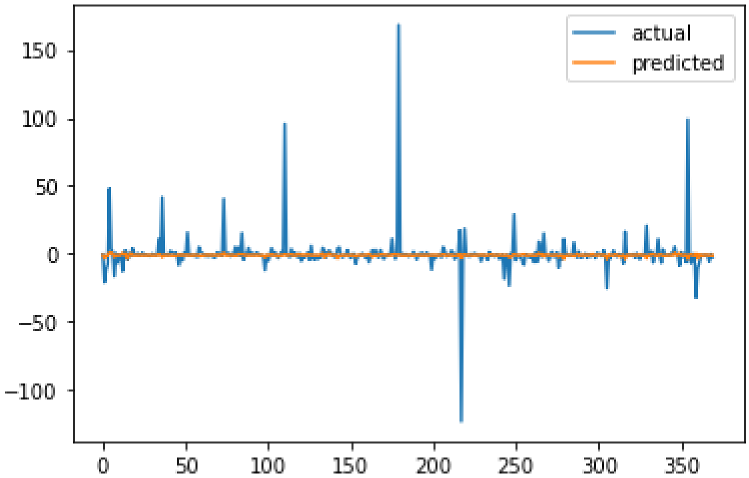
	MAE
35	4.18486

In [38]:

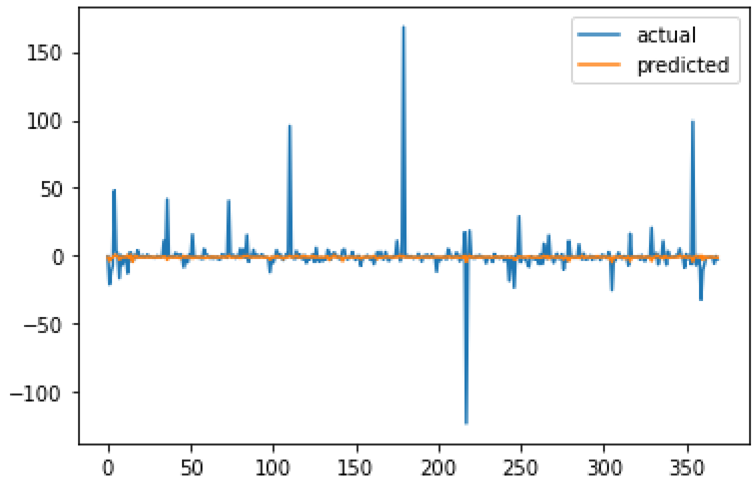
```
dropout_lst = np.arange(0, 1, 0.05)
dropout_dic = {}

for dropout in dropout_lst:
    def this_build_model(inputs, output_size, neurons, activ_func="linear",
                         dropout=dropout, loss="mae", optimizer="adam"):
        model = Sequential()

        model.add(LSTM(neurons, input_shape=(inputs.shape[1], inputs.shape[2])))
        model.add(Dropout(dropout))
        model.add(Dense(units=output_size))
        model.add(Activation(activ_func))

        model.compile(loss="mae", optimizer=optimizer)
        return model

    split_date = "2020-06-01"
    print("split_date:", split_date)

    # Split the training and test set
    training_set, test_set = df[df["Date"] < split_date], df[df["Date"] >= split_date]
    training_set = training_set.drop(["Date"], 1)
    test_set = test_set.drop(["Date"], 1)

    # Create windows for training
    LSTM_training_inputs = []
    for i in range(len(training_set)-window_len):
        temp_set = training_set[i:(i+window_len)].copy()

        for col in list(temp_set):
            temp_set[col] = temp_set[col]/temp_set[col].iloc[0] - 1

        LSTM_training_inputs.append(temp_set)
    LSTM_training_inputs
    LSTM_training_outputs = (training_set["return"][window_len:].values/training_set[
        "return"][:-window_len].values)-1

    LSTM_training_inputs = [np.array(LSTM_training_input) for LSTM_training_input in LSTM_trai
    LSTM_training_inputs = np.array(LSTM_training_inputs)

    # Create windows for testing
    LSTM_test_inputs = []
    for i in range(len(test_set)-window_len):
        temp_set = test_set[i:(i+window_len)].copy()

        for col in list(temp_set):
            temp_set[col] = temp_set[col]/temp_set[col].iloc[0] - 1

        LSTM_test_inputs.append(temp_set)
    LSTM_test_outputs = (test_set["return"][window_len:].values/test_set["return"][:-window_ler

    LSTM_test_inputs = [np.array(LSTM_test_inputs) for LSTM_test_inputs in LSTM_test_inputs]
    LSTM_test_inputs = np.array(LSTM_test_inputs)

    # initialise model architecture
    nn_model = this_build_model(LSTM_training_inputs, output_size=1, neurons = 32)
    # model output is next price normalised to 10th previous closing price train model on data
    # note: eth_history contains information on the training error per epoch
    nn_history = nn_model.fit(LSTM_training_inputs, LSTM_training_outputs,
```

```
                                epochs=5, batch_size=1, verbose=2, shuffle=True)
    plt.plot(LSTM_test_outputs, label = "actual")
    plt.plot(nn_model.predict(LSTM_test_inputs), label = "predicted")
    plt.legend()
    plt.show()
    MAE = mean_absolute_error(LSTM_test_outputs, nn_model.predict(LSTM_test_inputs))
    dropout_dic[dropout] = MAE
dropout_result = pd.DataFrame(dropout_dic.values(), dropout_dic.keys()).rename(columns={0: "MAE
```

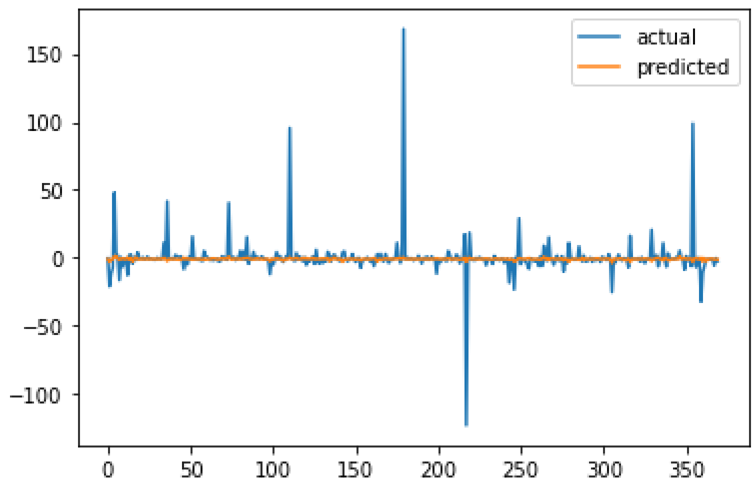
```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 10s - loss: 9.4342 - 10s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4217 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4170 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4109 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4048 - 8s/epoch - 2ms/step
```



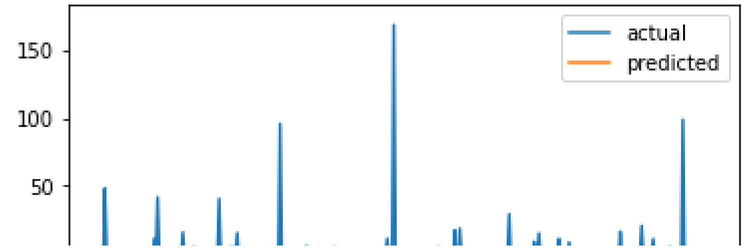

```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 9s - loss: 9.4362 - 9s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 9s - loss: 9.4251 - 9s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 9s - loss: 9.4208 - 9s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 9s - loss: 9.4154 - 9s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 9s - loss: 9.4090 - 9s/epoch - 2ms/step
```



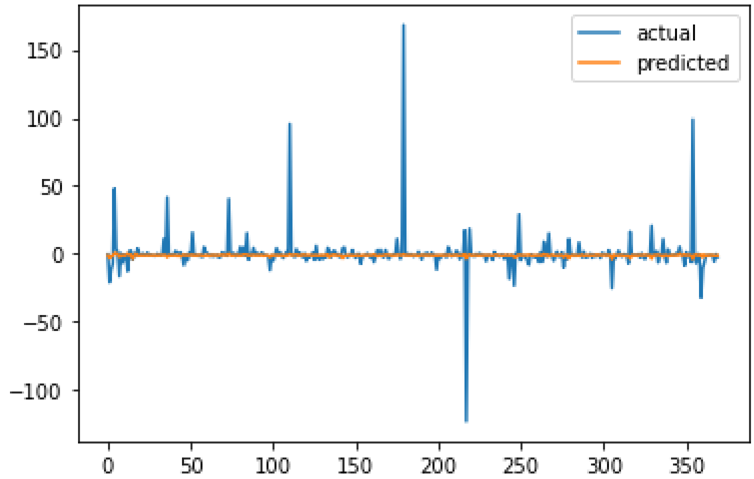

```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 9s - loss: 9.4402 - 9s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4254 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4203 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4152 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4103 - 8s/epoch - 2ms/step
```




```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 8s - loss: 9.4386 - 8s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4273 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4197 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4190 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4128 - 8s/epoch - 2ms/step
```

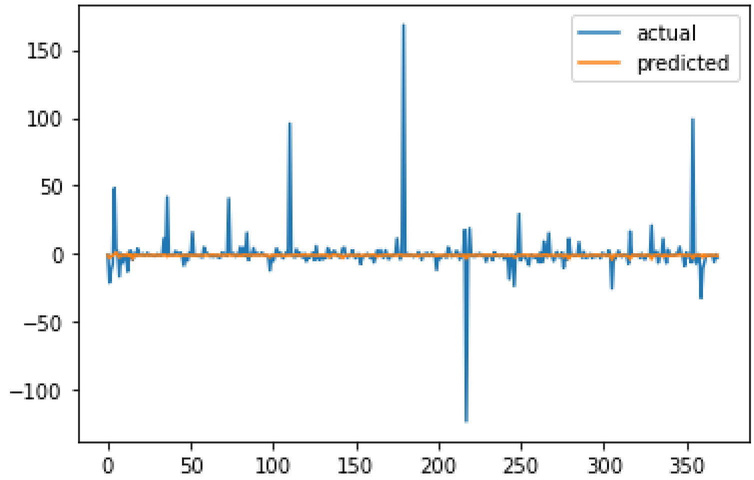



```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 8s - loss: 9.4423 - 8s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4306 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4268 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4246 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 9s - loss: 9.4107 - 9s/epoch - 2ms/step
```

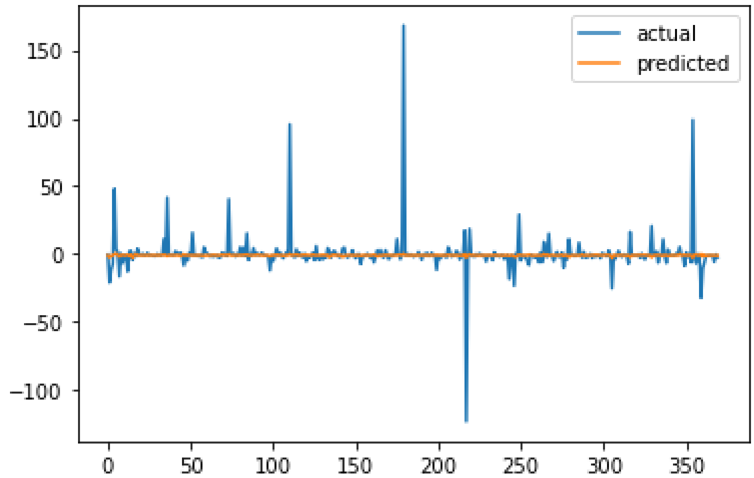



```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 10s - loss: 9.4429 - 10s/epoch - 3ms/step
Epoch 2/5
3967/3967 - 9s - loss: 9.4302 - 9s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 9s - loss: 9.4242 - 9s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4175 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4145 - 8s/epoch - 2ms/step
```

```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 9s - loss: 9.4452 - 9s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4339 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4206 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 9s - loss: 9.4204 - 9s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 9s - loss: 9.4132 - 9s/epoch - 2ms/step
```

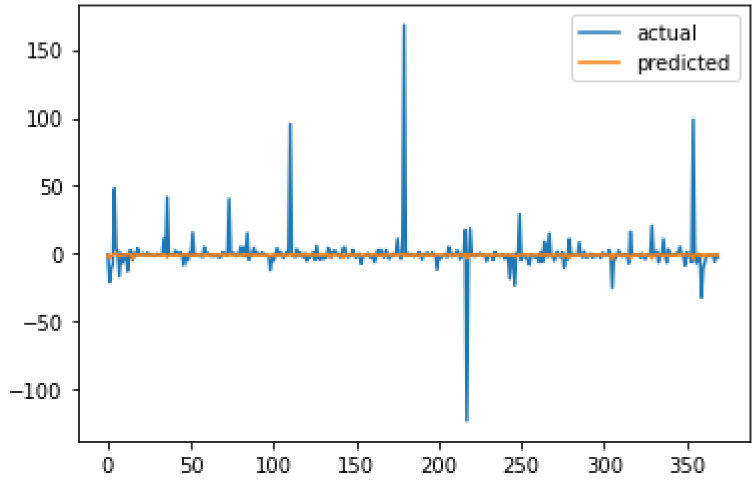



```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 10s - loss: 9.4402 - 10s/epoch - 3ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4312 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 9s - loss: 9.4201 - 9s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4216 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4149 - 8s/epoch - 2ms/step
```

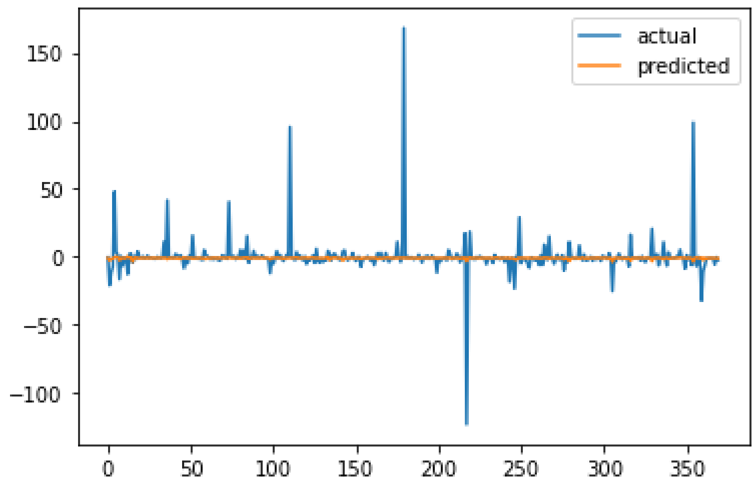



```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 10s - loss: 9.4358 - 10s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 9s - loss: 9.4371 - 9s/epoch - 2ms/step
```

```
Epoch 3/5
3967/3967 - 8s - loss: 9.4277 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4230 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 9s - loss: 9.4191 - 9s/epoch - 2ms/step
```

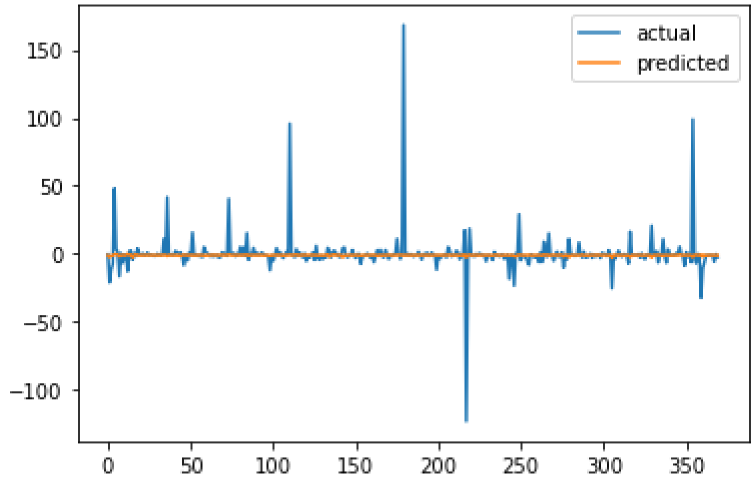



```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 9s - loss: 9.4505 - 9s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 9s - loss: 9.4285 - 9s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 10s - loss: 9.4281 - 10s/epoch - 3ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4211 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4207 - 8s/epoch - 2ms/step
```

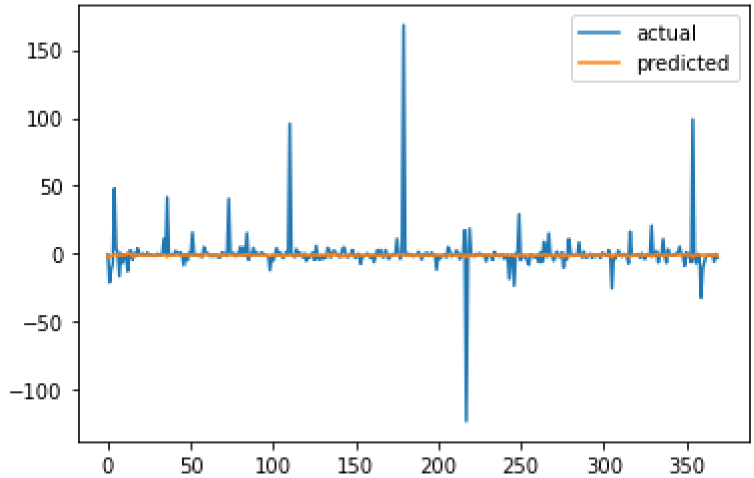



```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 10s - loss: 9.4483 - 10s/epoch - 3ms/step
Epoch 2/5
```

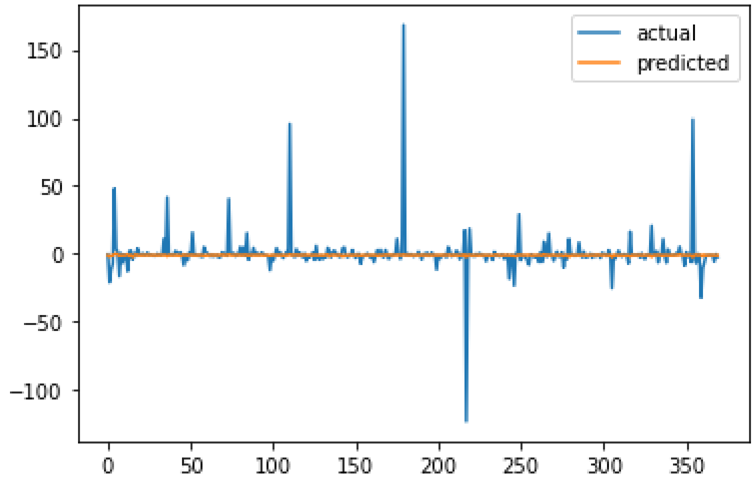
```
3967/3967 - 9s - loss: 9.4379 - 9s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 10s - loss: 9.4351 - 10s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 9s - loss: 9.4331 - 9s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 10s - loss: 9.4263 - 10s/epoch - 2ms/step
```



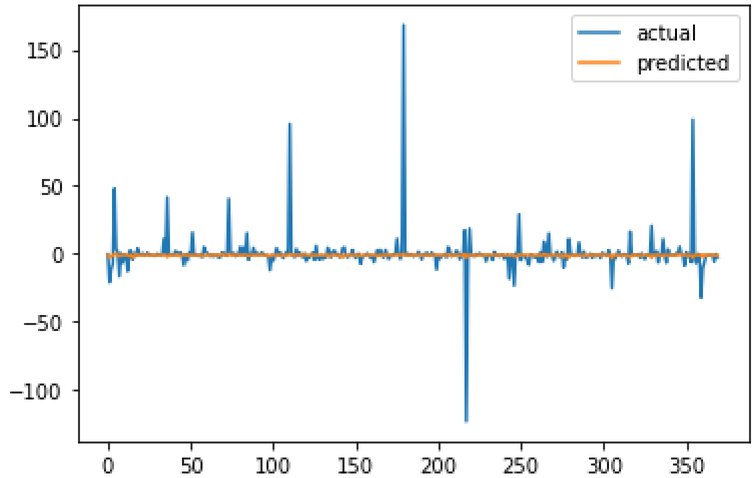

```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 11s - loss: 9.4525 - 11s/epoch - 3ms/step
Epoch 2/5
3967/3967 - 9s - loss: 9.4392 - 9s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4259 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4269 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4251 - 8s/epoch - 2ms/step
```



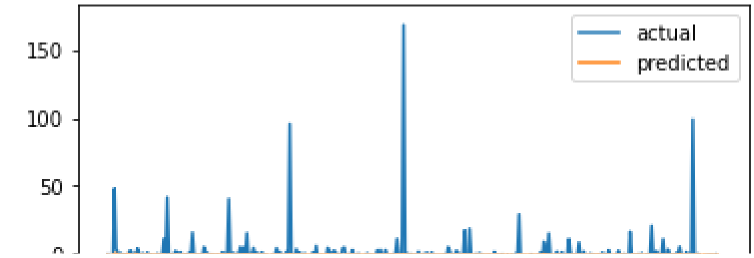

```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 8s - loss: 9.4622 - 8s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4326 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4383 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4316 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 7s - loss: 9.4240 - 7s/epoch - 2ms/step
```



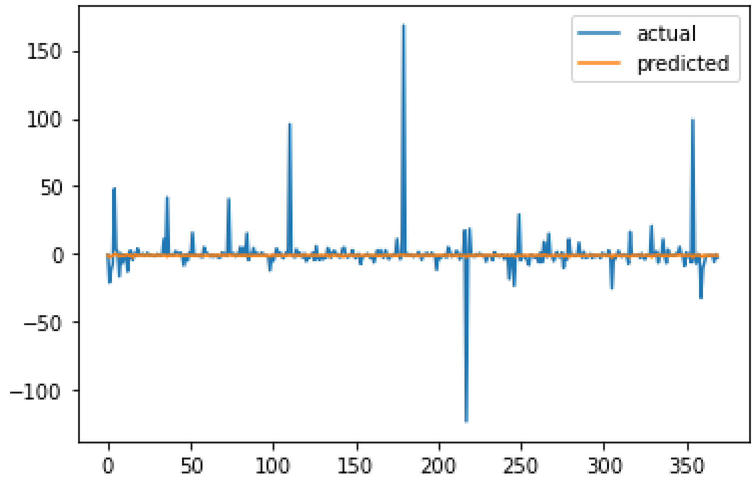
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 8s - loss: 9.4577 - 8s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4373 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4427 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4200 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4205 - 8s/epoch - 2ms/step



split_date: 2020-06-01
Epoch 1/5
3967/3967 - 9s - loss: 9.4673 - 9s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4398 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 9s - loss: 9.4242 - 9s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 8s - loss: 9.4244 - 8s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 9s - loss: 9.4205 - 9s/epoch - 2ms/step

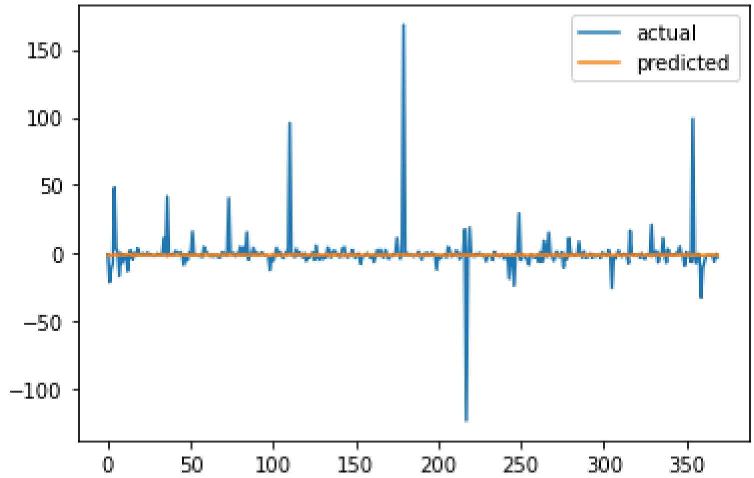



```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 9s - loss: 9.4714 - 9s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 9s - loss: 9.4424 - 9s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4333 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 9s - loss: 9.4316 - 9s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 9s - loss: 9.4246 - 9s/epoch - 2ms/step
```



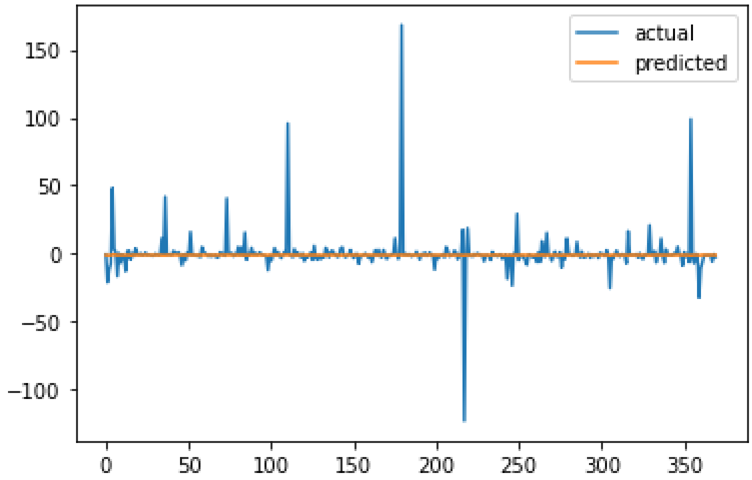

```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 9s - loss: 9.4788 - 9s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4408 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 9s - loss: 9.4344 - 9s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 10s - loss: 9.4263 - 10s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 9s - loss: 9.4242 - 9s/epoch - 2ms/step
```

```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 9s - loss: 9.4876 - 9s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4472 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4343 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 9s - loss: 9.4251 - 9s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4170 - 8s/epoch - 2ms/step
```




```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 9s - loss: 9.5018 - 9s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 9s - loss: 9.4419 - 9s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 9s - loss: 9.4367 - 9s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 10s - loss: 9.4320 - 10s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 9s - loss: 9.4229 - 9s/epoch - 2ms/step
```

```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 9s - loss: 9.5215 - 9s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4535 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4309 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 9s - loss: 9.4299 - 9s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4325 - 8s/epoch - 2ms/step
```



In [41]:

```
dropout_result[dropout_result==dropout_result.min()].dropna()
```

Out[41]:

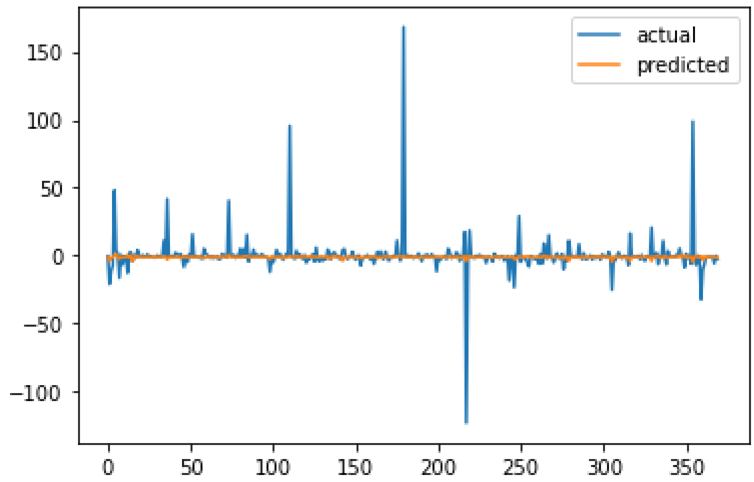
	MAE
0.4	4.187469

In [43]:

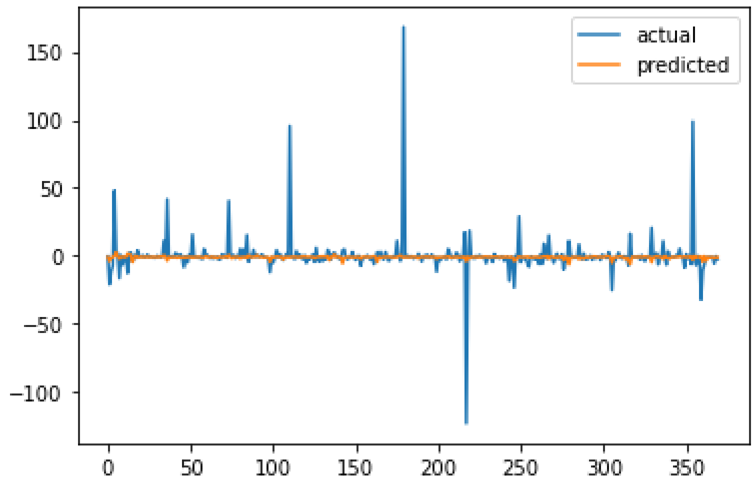
```
epochs_lst = np.arange(5, 25, 5)
epochs_dic = {}

for epochs in epochs_lst:
    def this_build_model(inputs, output_size, neurons, activ_func="linear",
                         dropout=0.10, loss="mae", optimizer="adam"):
        model = Sequential()

        model.add(LSTM(neurons, input_shape=(inputs.shape[1], inputs.shape[2])))
        model.add(Dropout(dropout))
        model.add(Dense(units=output_size))
        model.add(Activation(activ_func))

        model.compile(loss="mae", optimizer=optimizer)
        return model

    split_date = "2020-06-01"
    print("split_date:",split_date)

    #Split the training and test set
    training_set, test_set = df[df["Date"] < split_date], df[df["Date"] >= split_date]
    training_set = training_set.drop(["Date"], 1)
    test_set = test_set.drop(["Date"], 1)

    #Create windows for training
    LSTM_training_inputs = []
    for i in range(len(training_set)-window_len):
        temp_set = training_set[i:(i+window_len)].copy()

        for col in list(temp_set):
            temp_set[col] = temp_set[col]/temp_set[col].iloc[0] - 1

        LSTM_training_inputs.append(temp_set)
    LSTM_training_inputs
    LSTM_training_outputs = (training_set["return"][window_len:].values/training_set[
        "return"][:-window_len].values)-1

    LSTM_training_inputs = [np.array(LSTM_training_input) for LSTM_training_input in LSTM_trai
    LSTM_training_inputs = np.array(LSTM_training_inputs)

    # Create windows for testing
    LSTM_test_inputs = []
    for i in range(len(test_set)-window_len):
        temp_set = test_set[i:(i+window_len)].copy()

        for col in list(temp_set):
            temp_set[col] = temp_set[col]/temp_set[col].iloc[0] - 1

        LSTM_test_inputs.append(temp_set)
    LSTM_test_outputs = (test_set["return"][window_len:].values/test_set["return"][:-window_ler

    LSTM_test_inputs = [np.array(LSTM_test_inputs) for LSTM_test_inputs in LSTM_test_inputs]
    LSTM_test_inputs = np.array(LSTM_test_inputs)

    # initialise model architecture
    nn_model = this_build_model(LSTM_training_inputs, output_size=1, neurons = 32)
    # model output is next price normalised to 10th previous closing price train model on data
    # note: eth_history contains information on the training error per epoch
    nn_history = nn_model.fit(LSTM_training_inputs, LSTM_training_outputs,
```

```
                                      epochs=epochs, batch_size=1, verbose=2, shuffle=True)
    plt.plot(LSTM_test_outputs, label = "actual")
    plt.plot(nn_model.predict(LSTM_test_inputs), label = "predicted")
    plt.legend()
    plt.show()
    MAE = mean_absolute_error(LSTM_test_outputs, nn_model.predict(LSTM_test_inputs))
    epochs_dic[epochs] = MAE
epochs_result = pd.DataFrame(epochs_dic.values(), epochs_dic.keys()).rename(columns={0: "MAE"})
```

```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 9s - loss: 9.4361 - 9s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4241 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 9s - loss: 9.4200 - 9s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 9s - loss: 9.4138 - 9s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 8s - loss: 9.4076 - 8s/epoch - 2ms/step
```

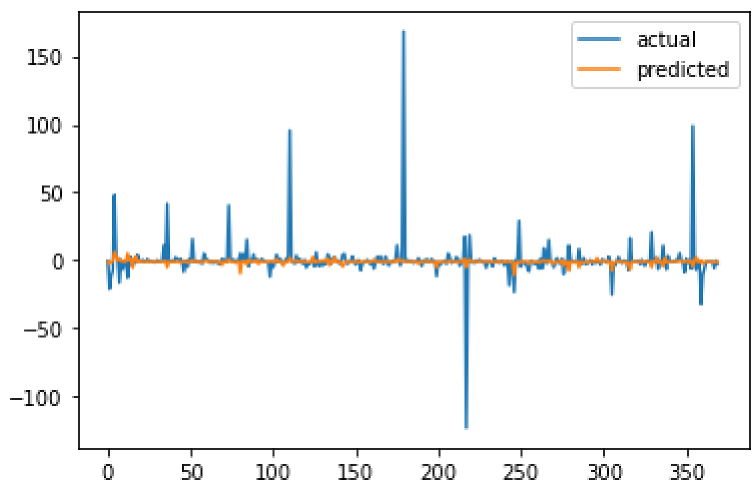



```
split_date: 2020-06-01
Epoch 1/10
3967/3967 - 9s - loss: 9.4331 - 9s/epoch - 2ms/step
Epoch 2/10
3967/3967 - 8s - loss: 9.4275 - 8s/epoch - 2ms/step
Epoch 3/10
3967/3967 - 9s - loss: 9.4179 - 9s/epoch - 2ms/step
Epoch 4/10
3967/3967 - 9s - loss: 9.4170 - 9s/epoch - 2ms/step
Epoch 5/10
3967/3967 - 10s - loss: 9.4077 - 10s/epoch - 2ms/step
Epoch 6/10
3967/3967 - 8s - loss: 9.4005 - 8s/epoch - 2ms/step
Epoch 7/10
3967/3967 - 8s - loss: 9.3948 - 8s/epoch - 2ms/step
Epoch 8/10
3967/3967 - 10s - loss: 9.3868 - 10s/epoch - 2ms/step
Epoch 9/10
3967/3967 - 8s - loss: 9.3789 - 8s/epoch - 2ms/step
Epoch 10/10
3967/3967 - 8s - loss: 9.3691 - 8s/epoch - 2ms/step
```




```
split_date: 2020-06-01
Epoch 1/15
3967/3967 - 9s - loss: 9.4326 - 9s/epoch - 2ms/step
Epoch 2/15
3967/3967 - 9s - loss: 9.4269 - 9s/epoch - 2ms/step
Epoch 3/15
3967/3967 - 9s - loss: 9.4220 - 9s/epoch - 2ms/step
Epoch 4/15
3967/3967 - 10s - loss: 9.4221 - 10s/epoch - 2ms/step
Epoch 5/15
3967/3967 - 8s - loss: 9.4191 - 8s/epoch - 2ms/step
Epoch 6/15
3967/3967 - 9s - loss: 9.4060 - 9s/epoch - 2ms/step
Epoch 7/15
3967/3967 - 8s - loss: 9.4021 - 8s/epoch - 2ms/step
Epoch 8/15
3967/3967 - 9s - loss: 9.3902 - 9s/epoch - 2ms/step
Epoch 9/15
3967/3967 - 8s - loss: 9.3812 - 8s/epoch - 2ms/step
Epoch 10/15
3967/3967 - 8s - loss: 9.3683 - 8s/epoch - 2ms/step
Epoch 11/15
3967/3967 - 8s - loss: 9.3663 - 8s/epoch - 2ms/step
Epoch 12/15
3967/3967 - 8s - loss: 9.3466 - 8s/epoch - 2ms/step
Epoch 13/15
3967/3967 - 8s - loss: 9.3479 - 8s/epoch - 2ms/step
Epoch 14/15
3967/3967 - 8s - loss: 9.3218 - 8s/epoch - 2ms/step
Epoch 15/15
3967/3967 - 8s - loss: 9.3113 - 8s/epoch - 2ms/step
```

```
split_date: 2020-06-01
Epoch 1/20
3967/3967 - 9s - loss: 9.4432 - 9s/epoch - 2ms/step
Epoch 2/20
3967/3967 - 8s - loss: 9.4292 - 8s/epoch - 2ms/step
Epoch 3/20
3967/3967 - 9s - loss: 9.4216 - 9s/epoch - 2ms/step
Epoch 4/20
3967/3967 - 8s - loss: 9.4177 - 8s/epoch - 2ms/step
Epoch 5/20
3967/3967 - 8s - loss: 9.4116 - 8s/epoch - 2ms/step
Epoch 6/20
3967/3967 - 8s - loss: 9.4085 - 8s/epoch - 2ms/step
Epoch 7/20
3967/3967 - 8s - loss: 9.4012 - 8s/epoch - 2ms/step
Epoch 8/20
3967/3967 - 8s - loss: 9.3837 - 8s/epoch - 2ms/step
Epoch 9/20
3967/3967 - 8s - loss: 9.3852 - 8s/epoch - 2ms/step
Epoch 10/20
3967/3967 - 9s - loss: 9.3723 - 9s/epoch - 2ms/step
Epoch 11/20
3967/3967 - 10s - loss: 9.3635 - 10s/epoch - 2ms/step
Epoch 12/20
3967/3967 - 9s - loss: 9.3492 - 9s/epoch - 2ms/step
Epoch 13/20
3967/3967 - 9s - loss: 9.3352 - 9s/epoch - 2ms/step
Epoch 14/20
3967/3967 - 8s - loss: 9.3159 - 8s/epoch - 2ms/step
Epoch 15/20
3967/3967 - 8s - loss: 9.2988 - 8s/epoch - 2ms/step
Epoch 16/20
3967/3967 - 9s - loss: 9.2870 - 9s/epoch - 2ms/step
Epoch 17/20
3967/3967 - 9s - loss: 9.2569 - 9s/epoch - 2ms/step
Epoch 18/20
3967/3967 - 9s - loss: 9.2422 - 9s/epoch - 2ms/step
Epoch 19/20
3967/3967 - 8s - loss: 9.2103 - 8s/epoch - 2ms/step
Epoch 20/20
3967/3967 - 8s - loss: 9.2087 - 8s/epoch - 2ms/step
```



In [45]:

```
epochs_result[epochs_result == epochs_result.min()].dropna()
```

Out[45]:

	MAE
5	4.203348

Conclusion

In [47]:

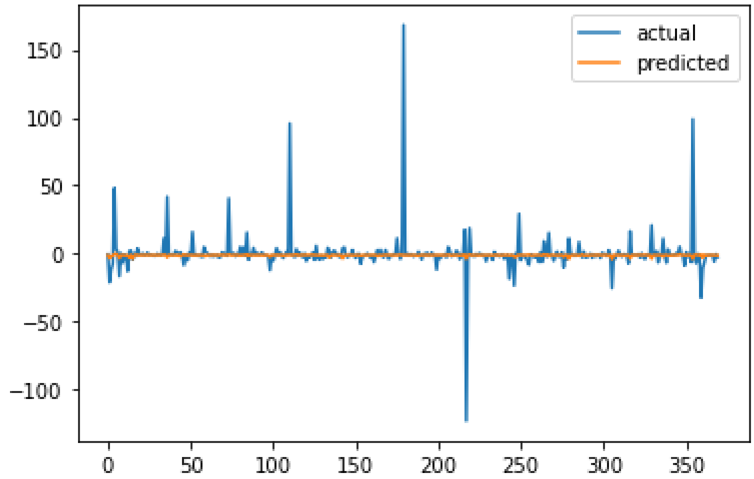
```
window = 11
neurons = 35
dropout = 0.4
epochs = 5
```

In [48]:

```
def test_build_model(inputs, output_size, neurons, activ_func="linear",
                     dropout=dropout, loss="mae", optimizer="adam"):
    model = Sequential()
    model.add(LSTM(neurons, input_shape=(inputs.shape[1], inputs.shape[2])))
    model.add(Dropout(dropout))
    model.add(Dense(units=output_size))
    model.add(Activation(activ_func))
    model.compile(loss=loss, optimizer=optimizer)
    return model

split_date = "2020-06-01"
print("split_date:",split_date)

# Split the training and test set
training_set, test_set = df[df["Date"] < split_date], df[df["Date"] >= split_date]
training_set = training_set.drop(["Date"], 1)
test_set = test_set.drop(["Date"], 1)

# Create windows for training
LSTM_training_inputs = []
for i in range(len(training_set)-window_len):
    temp_set = training_set[i:(i+window_len)].copy()

    for col in list(temp_set):
        temp_set[col] = temp_set[col]/temp_set[col].iloc[0] - 1
    LSTM_training_inputs.append(temp_set)

LSTM_training_inputs
LSTM_training_outputs = (training_set["return"][window_len:].values/training_set[
    "return"][:-window_len].values)-1

LSTM_training_inputs = [np.array(LSTM_training_input) for LSTM_training_input in LSTM_training
LSTM_training_inputs = np.array(LSTM_training_inputs)

# Create windows for testing
LSTM_test_inputs = []
for i in range(len(test_set)-window_len):
    temp_set = test_set[i:(i+window_len)].copy()

    for col in list(temp_set):
        temp_set[col] = temp_set[col]/temp_set[col].iloc[0] - 1

    LSTM_test_inputs.append(temp_set)
LSTM_test_outputs = (test_set["return"][window_len:].values/test_set["return"][:-window_len].va

LSTM_test_inputs = [np.array(LSTM_test_inputs) for LSTM_test_inputs in LSTM_test_inputs]
LSTM_test_inputs = np.array(LSTM_test_inputs)

# initialise model architecture
nn_model = test_build_model(LSTM_training_inputs, output_size=1, neurons = neurons)
# model output is next price normalised to 10th previous closing price train model on data
# note: eth_history contains information on the training error per epoch
nn_history = nn_model.fit(LSTM_training_inputs, LSTM_training_outputs,
                          epochs=epochs, batch_size=1, verbose=2, shuffle=True)
plt.plot(LSTM_test_outputs, label = "actual")
plt.plot(nn_model.predict(LSTM_test_inputs), label = "predicted")
plt.legend()
plt.show()
MAE = mean_absolute_error(LSTM_test_outputs, nn_model.predict(LSTM_test_inputs))
```

```
print("MAE: ", MAE)
```

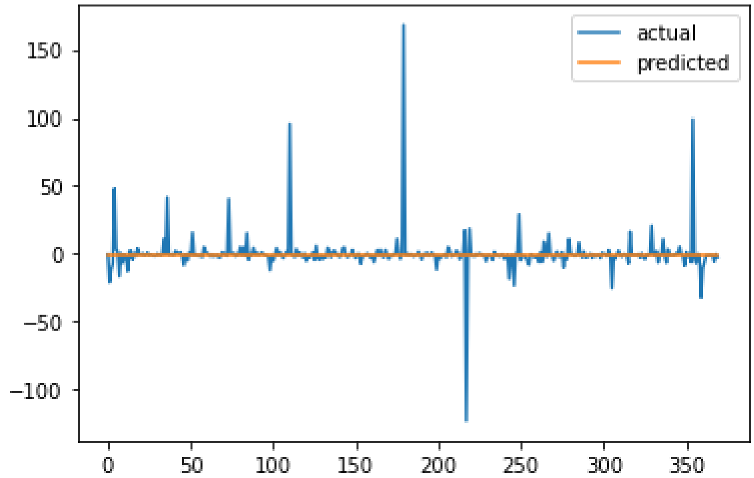
```
split_date: 2020-06-01
Epoch 1/5
3967/3967 - 10s - loss: 9.4475 - 10s/epoch - 2ms/step
Epoch 2/5
3967/3967 - 8s - loss: 9.4348 - 8s/epoch - 2ms/step
Epoch 3/5
3967/3967 - 8s - loss: 9.4288 - 8s/epoch - 2ms/step
Epoch 4/5
3967/3967 - 9s - loss: 9.4232 - 9s/epoch - 2ms/step
Epoch 5/5
3967/3967 - 9s - loss: 9.4188 - 9s/epoch - 2ms/step
```




```
MAE:  4.20413225628425
```

In [49]:

```
def predict_sequence_full(model, data, window_size):
    #Shift the window by 1 new prediction each time, re-run predictions on new window
    curr_frame = data[0]
    predicted = []
    for i in range(len(data)):
        predicted.append(model.predict(curr_frame[np.newaxis,:,:])[0,0])
        curr_frame = curr_frame[1:]
        curr_frame = np.insert(curr_frame, [window_size-1], predicted[-1], axis=0)
    return predicted

predictions = predict_sequence_full(nn_model, LSTM_test_inputs, 10)

plt.plot(LSTM_test_outputs, label="actual")
plt.plot(predictions, label="predicted")
plt.legend()
plt.show()
MAE = mean_absolute_error(LSTM_test_outputs, predictions)
print('The Mean Absolute Error is: {}'.format(MAE))
```




```
The Mean Absolute Error is: 4.202302719465017
```

In [ ]:

```

```