Price_Development_Analysis

May 24, 2022

1 Compare Changes in the Graph with Current Price Data

Load here the needed libraries and data. Also, filter the data we treat. Finally, choose a time window by computing a column e.g. days, days with hour, etc.

[16]:
```
import sys

import pandas as pd
import networkx as nx
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import numpy as np

from degree_centrality import DegreeCentrality
from current_price_fetcher import CurrentPriceFetcher

pd.set_option('display.max_rows', 50)
pd.set_option('display.max_columns', None)
```

Load the edgelist into a pandas frame for preprocessing.

[17]:
```
edges = pd.read_csv('../data/csv/edges_deep_link_no_merge.csv')

#prepare human readable time
edges['human_time'] = pd.to_datetime(edges['time'], unit='s').dt.date
edges['human_time_hour'] = pd.to_datetime(edges['time'], unit='s').dt.
↪strftime('%Y-%m-%d %H')

#filter data from to
date_from = pd.to_datetime("2022-4-1").date()
date_to = pd.to_datetime("2022-5-24").date()
frame = edges[(edges['human_time'] >= date_from) & (edges['human_time'] <␣
↪date_to)]

data = frame.sort_values(by='time')

data
```

[17]:
```
                 source               target  score  weight          time  \
60362        chadtastic   NeedleworkerNo2874      1     1.0  1.648772e+09
60363       BrubMomento   NeedleworkerNo2874      1     1.0  1.648773e+09
26413           AESTHTK             Solodeji     24    24.0  1.648773e+09
26404    tommyjangles22             muradphy      3     3.0  1.648773e+09
59990          noctis89   NeedleworkerNo2874      0     0.0  1.648773e+09
…                 …                    …     …       …           …
113487          Heph333           notdsylexic      1     0.5  1.653350e+09
113486          Heph333          PumperNikel0      1     1.0  1.653350e+09
113485          Heph333         PusghettiBoy93      1     1.0  1.653350e+09
48931          Romando1  Black_Labs_Matter69      4     4.0  1.653350e+09
216544      Safe-You134             OGBernard      2     2.0  1.653350e+09

              sub  human_time human_time_hour
60362     Bitcoin  2022-04-01   2022-04-01 00
60363     Bitcoin  2022-04-01   2022-04-01 00
26413    Ethereum  2022-04-01   2022-04-01 00
26404    Ethereum  2022-04-01   2022-04-01 00
59990     Bitcoin  2022-04-01   2022-04-01 00
…           …          …              …
113487    Bitcoin  2022-05-23   2022-05-23 23
113486    Bitcoin  2022-05-23   2022-05-23 23
113485    Bitcoin  2022-05-23   2022-05-23 23
48931     Bitcoin  2022-05-23   2022-05-23 23
216544   Dogecoin  2022-05-23   2022-05-23 23

[217172 rows x 8 columns]
```

Preprocessing: Activity computation

We want to analyze graph development, i.e. the interactions over time. To do so, we will create a list of cumulitative subsets which correspond to a time window. Each subset is a subset of the next time window, i.e. $day[0] \subset day[1]$...

[18]:
```python
# returns [(date1,pd frame1), (date1,pd frame2), (date1,pd frame3)...]
# pass key fct to overwrite key (date1,...)

def increasing_table_inclusion(df, by='human_time', key=None):
    disj_days = list(df.groupby(by, as_index=False))

    first_day = disj_days[0]
    first_key = key(0, first_day) if key is not None else first_day[0]

    cumulated = [ (first_key,first_day[1]) ]

    for i, day in enumerate(disj_days,start=0):
        if i > 0: #skip first day
            i_key = key(i, day) if key is not None else day[0]
```

```
            frame_so_far = pd.concat([cumulated[i-1][1], day[1]])
            cumulated.append(
                (i_key,
                 frame_so_far
                )
            )

    return cumulated
```

Now, let's create networkx graph instances of these edgelists to analyze them.

[19]:
```
Gs = []
time_key = lambda _,d: pd.to_datetime(f'{d[0]}:00')

for time, cum_days in increasing_table_inclusion(data, by="human_time_hour"):
    Gs.append(
        (time,
         nx.from_pandas_edgelist(
             cum_days, create_using=nx.MultiDiGraph(), source='source',␣
 ↪target='target',
             edge_attr=['score', 'weight', 'time', 'sub'])
        )
    )
```

Next, we want to compute the differences between each timeframe. We provide here two possible difference functions. One in percentage and one in absolute value.

[20]:
```
def compute_diff_prc(row,col):
    old = row[f'{col}_old']
    new = row[f'{col}_new']

    if old > 0:
        return (new / old - 1) * 100
    else:
        return 0

def compute_diff_abs(row,col):
    old = row[f'{col}_old']
    new = row[f'{col}_new']

    return new - old

def compute_nodes_degree_difference(G1, G2, f=None, cols=None):
    dc = DegreeCentrality()
    df1 = dc.compute_degree_centrality(G1)
    df2 = dc.compute_degree_centrality(G2)

    if cols is None:
```

```
        cols = { col : [] for col in list(df2.columns)}

    if f is None:
        f = compute_diff_prc

    diff = pd.DataFrame(cols)

    j = df1.join(df2, how='inner', lsuffix='_old', rsuffix='_new')

    for col in cols:
        diff[col] = j.apply(lambda row: f(row,col), axis=1)

    s = j.reindex(sorted(j.columns), axis=1)

    diff.drop(labels=['[deleted]'], axis=0, inplace=True,errors='ignore')␣
  ↪#remove deleted posts


    return diff
```

Compute the differences.

Attention: This code block will require significant amount of time to compute and needs up to 50GB of RAM.

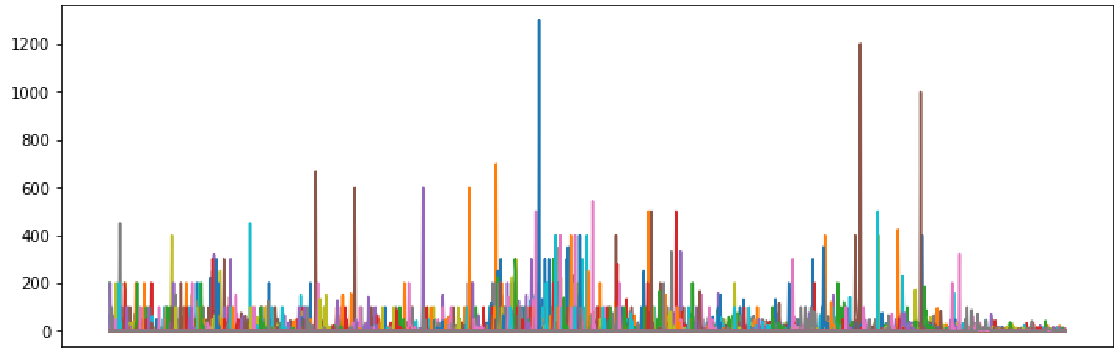
```
[21]: differences = [
          (Gs[i][0], #date
           compute_nodes_degree_difference(Gs[i][1], Gs[i+1][1], f=compute_diff_prc)␣
        ↪#frame
          )
          for i in range(len(Gs) - 1)
      ]
```

Finally, we can prepare our data for plotting

```
[50]: degrees_list = [ df.rename(columns={"degree": date} )[date] for date,df in␣
        ↪differences ]

      degrees = pd.concat(degrees_list, axis=1)

      #dropzero rows
      degrees = degrees.loc[~(degrees==0).all(axis=1)]

      #fill nan with 0
      degrees.fillna(0, inplace=True)
      degrees.reset_index(drop=True,inplace=True) #drop user names
```

Let's quickly reduce our data size to plot something meaningful

[53]:
```
cols = list(degrees.columns)
plot_data = degrees[np.count_nonzero(degrees.values, axis=1) > len(degrees.
 ↪columns)/30] #reduce for plotting
fig, ax = plt.subplots(figsize=(12, 4))
ax.set_xticks([], [])
plt.plot(plot_data.T)
plt.show()
```

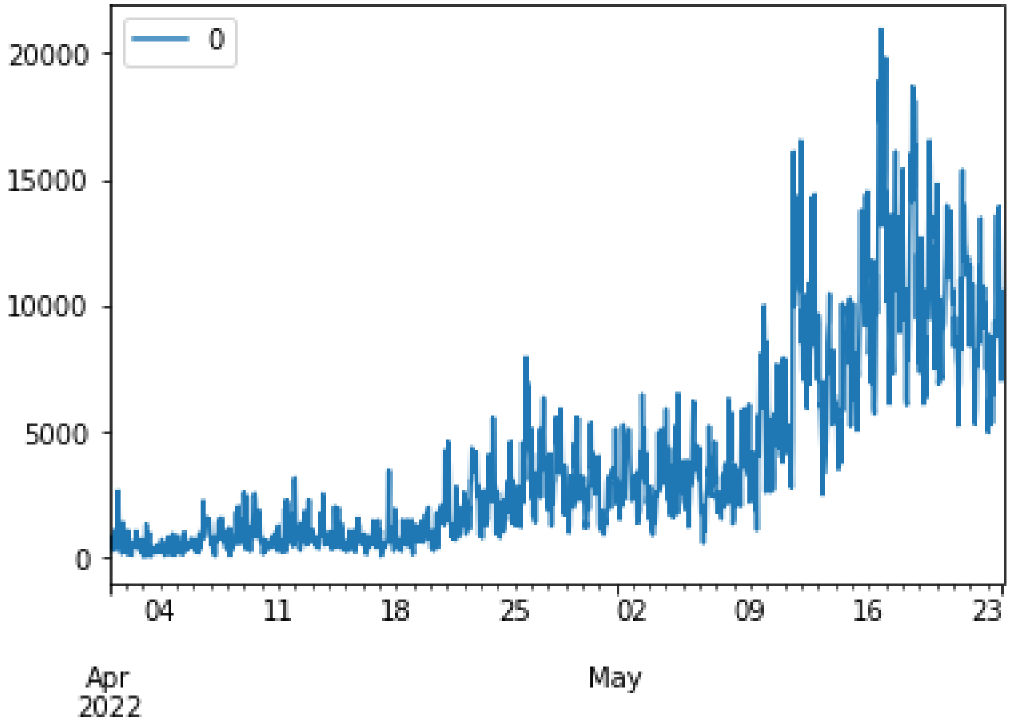


[54]:
```
degrees.to_csv("degrees.csv")
#degrees = pd.read_csv('degrees.csv', index_col=0) #use this to not recompute␣
 ↪degrees since it takes forever
```

Let's sum up each row and see how it develops; each row represents one user, each column represents one time window.

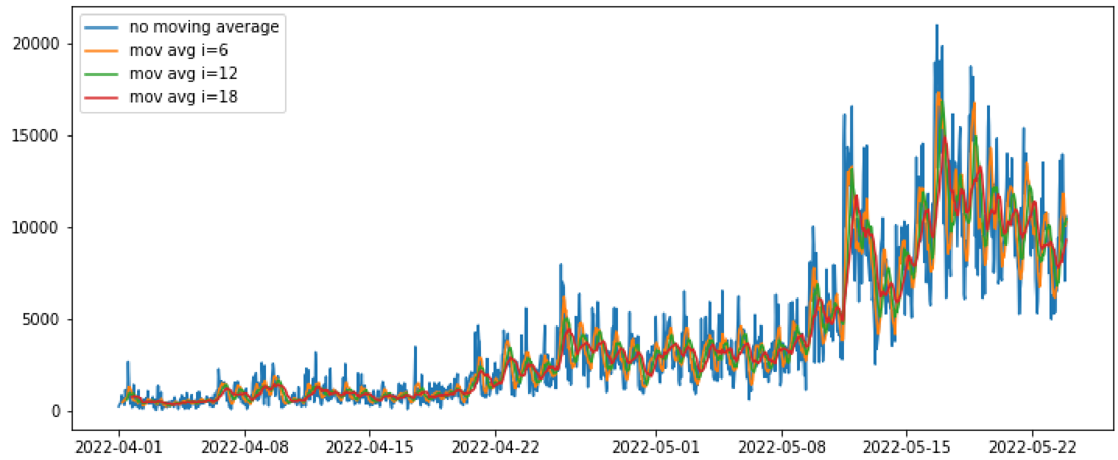
[275]:
```
sums = pd.DataFrame(degrees.apply(lambda col: sum(col), axis=0))
sums.index = pd.to_datetime(sums.index)

sums.plot()
```

[275]: <AxesSubplot:>



Compute & plot moving average.

[276]:
```
ma_windows = range(2,20) #compute for steps 2 to 20

ma_sums = pd.DataFrame({})

fig, ax = plt.subplots(figsize=(12, 5))

plt.plot(sums[0])
leg = ['no moving average']

ma_sums['ma_0'] = sums[0]

for i in ma_windows:
    ma_sums[f'ma_{i}'] = sums[0].rolling(i).mean()
    if i % 6 == 0:
        plt.plot(ma_sums[f'ma_{i}'])
        leg.append(f'mov avg i={i}')

plt.legend(leg)
plt.savefig('plots/sums_ma.pdf')
plt.show()
```

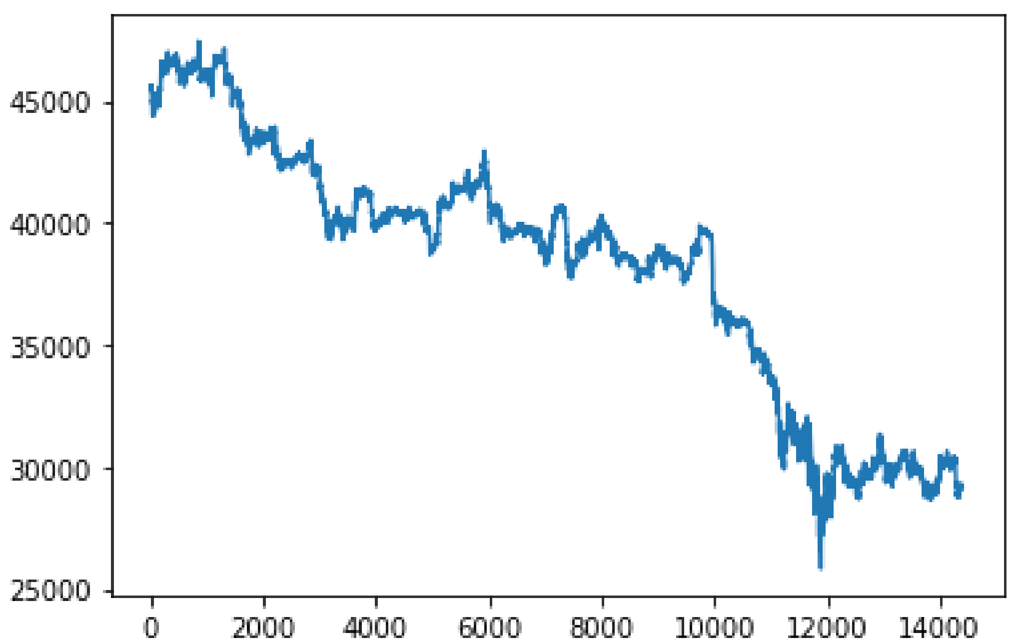


Preprocessing: Price computation

Load the price data and preprocess.

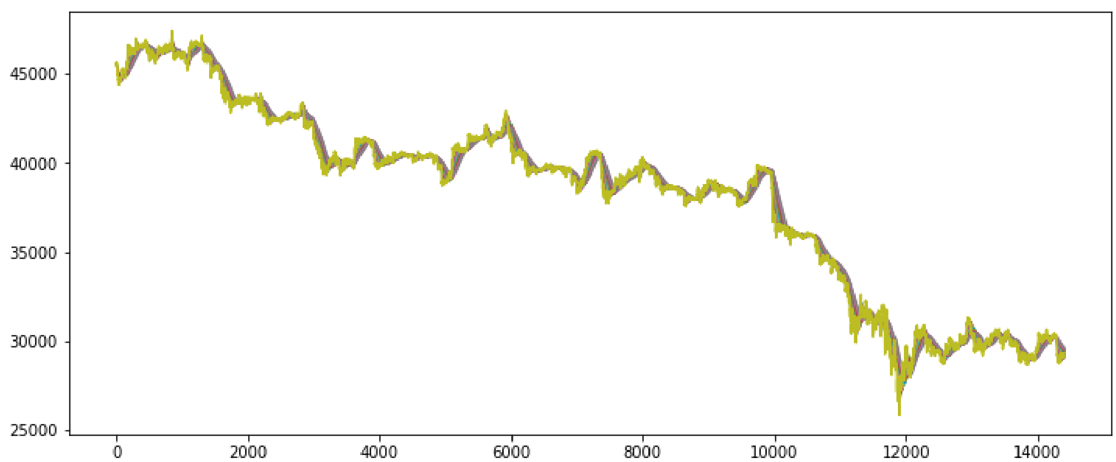
[277]:
```
df = pd.read_csv('../data/price/BTC-USD-2022-04-01.csv')
df['human_time'] = pd.to_datetime(df['unix'], unit='s').dt.date
df['human_time_hour'] = pd.to_datetime(df['unix'], unit='s').dt.
↪strftime('%Y-%m-%d %H')
frame = df[(df['human_time'] >= date_from) & (df['human_time'] < date_to)]
```

[278]:
```
plt.plot(frame['close'])

plt.show()
```



Compute moving average also for price.

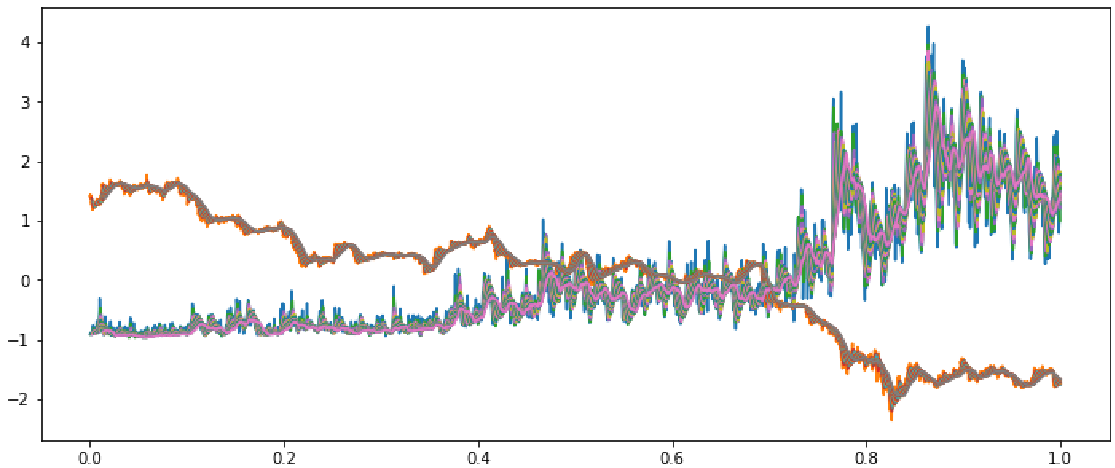
[279]:
```
ma_closes = pd.DataFrame({})
f = frame['close'] #column to use


ma_closes['ma_0'] = f

fig, ax = plt.subplots(figsize=(12, 5))

for i in ma_windows:

    step = (len(f)/len(sums)) #since len(closes) > len(sums) and we want to␣
 ↪roll "over the same time"
    ma_closes[f'ma_{i}'] = f.rolling(int(step*i)).mean()
    plt.plot(ma_closes[f'ma_{i}'])

plt.plot(ma_closes['ma_0'])


ma_closes['dt'] = pd.to_datetime(frame['unix'], unit='s')
ma_closes.set_index('dt', inplace=True)
```



Plot price over set of moving windows of sums.

[280]:
```
normalized_sums = (ma_sums-ma_sums.mean())/ma_sums.std()
normalized_closes = (ma_closes-ma_closes.mean())/ma_closes.std()
```

[281]:
```
l = list(ma_windows)
l.insert(0,0)

fig, ax = plt.subplots(figsize=(12, 5))

for i in l:
    x1 = np.linspace(0, 1, len(normalized_sums))
    x2 = np.linspace(0, 1, len(normalized_closes))

    plt.plot(x1, normalized_sums[f'ma_{i}'])
    plt.plot(x2, normalized_closes[f'ma_{i}'])

plt.show()
```



Finally, resample our data and then join.

[299]:
```
resampled = normalized_closes.resample('60min').mean()

joined_data = normalized_sums.join(resampled, how='inner', lsuffix='_activity',␣
↪rsuffix='_close')
```

1.1 Try to correlate

Let's facilitate our work by first writing some functions

[315]:
```
def compute_corr(df, method):
    r=[]
    for p in ma_windows:
        for a in ma_windows:
            pair = [f'ma_{p}_activity',f'ma_{a}_close']
            j = df[pair].dropna()
```

```
            corr = method(j)

            v = abs(corr[0][1]) + abs(corr[1][0])

            r.append((v,corr,j,pair))

    best_result = sorted(r, key=lambda tup: -tup[0])

    return best_result

def plot_corr(corr):
    corr[2].plot()

def spearman(df):
    return df.corr(method="spearman").values

def pearson(df):
    return df.corr(method="pearson").values

def kendall(df):
    return df.corr(method="kendall").values
```

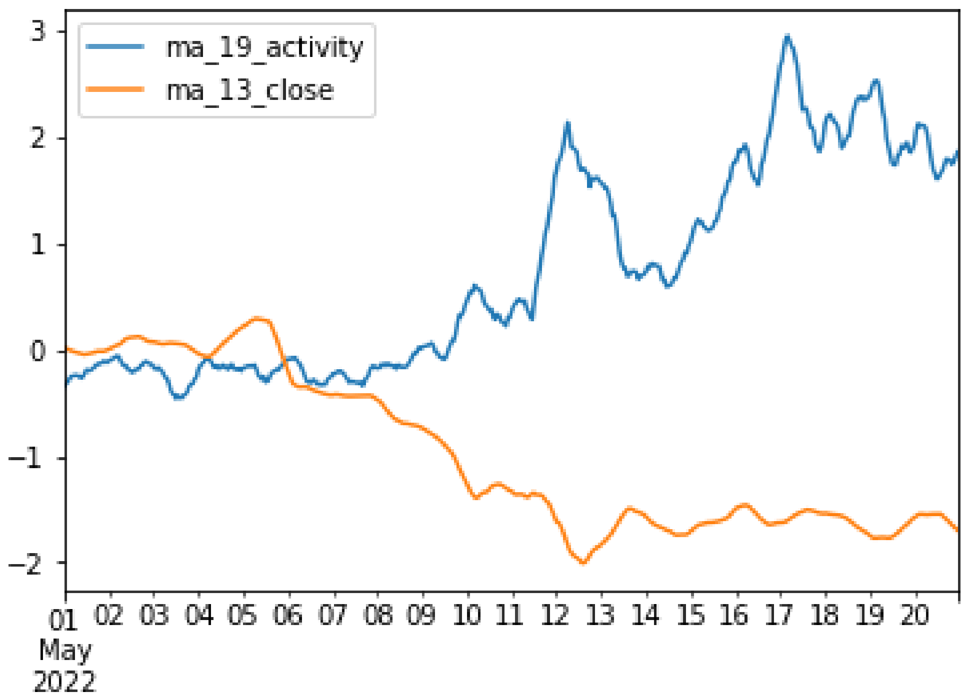
Set our dates from when to when we want to correlat the data

[311]:
```
fr = '2022-05-01 00:00:00'
to = '2022-05-23 00:00:00'
```

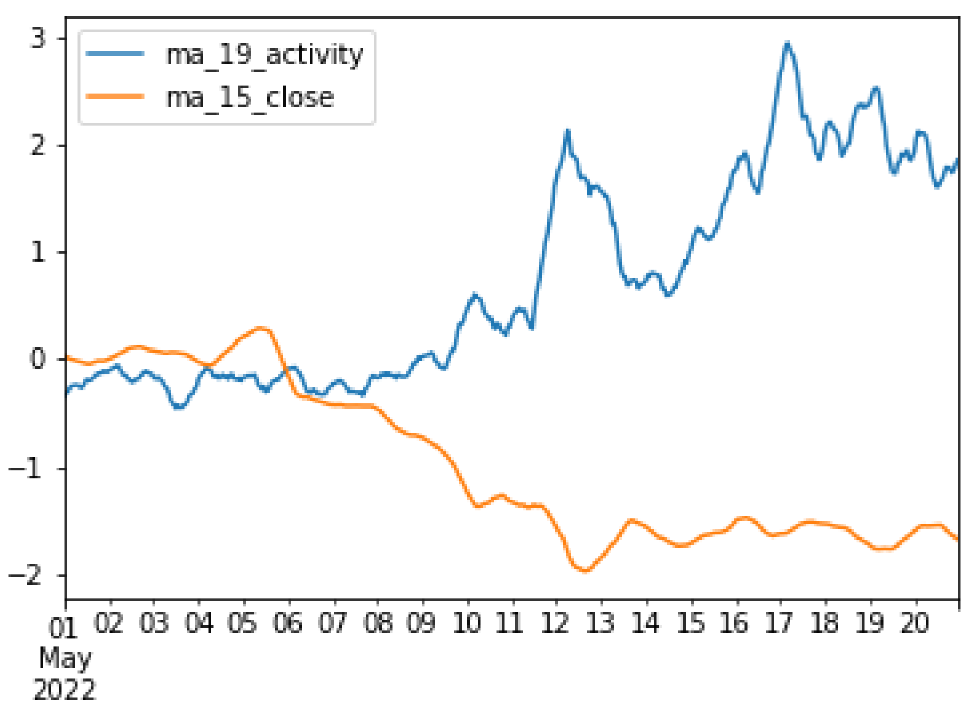
Now, let's compute the 5 best correlations for spearman

[317]:
```
d = joined_data[fr:to]
sp = compute_corr(d, spearman)
for i in range(3):
    s = sp[i]
    plot_corr(s)
    print(f"Correlation for {s[3]}:\n{s[1]}")
```

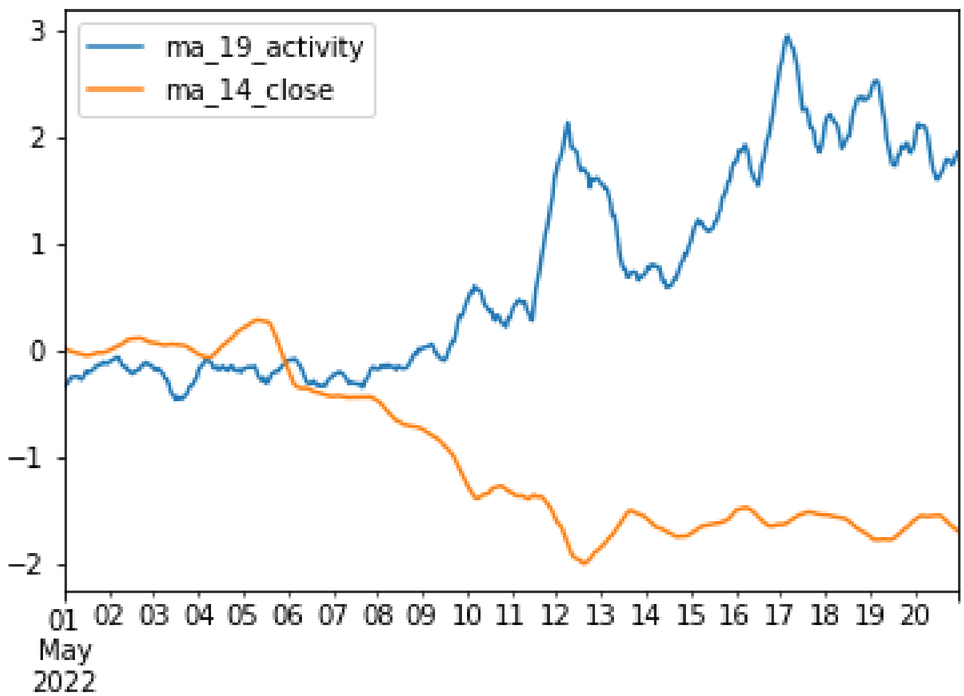
```
Correlation for ['ma_19_activity', 'ma_13_close']:
[[ 1.         -0.8368004]
 [-0.8368004  1.       ]]
Correlation for ['ma_19_activity', 'ma_15_close']:
[[ 1.          -0.83660378]
 [-0.83660378  1.        ]]
Correlation for ['ma_19_activity', 'ma_14_close']:
[[ 1.          -0.83658924]
 [-0.83658924  1.        ]]
```



ma_19_activity
ma_13_close
3
2
1
0
−1
−2
01
May
2022
02
03
04
05
06
07
08
09
10
11
12
13
14
15
16
17
18
19
20



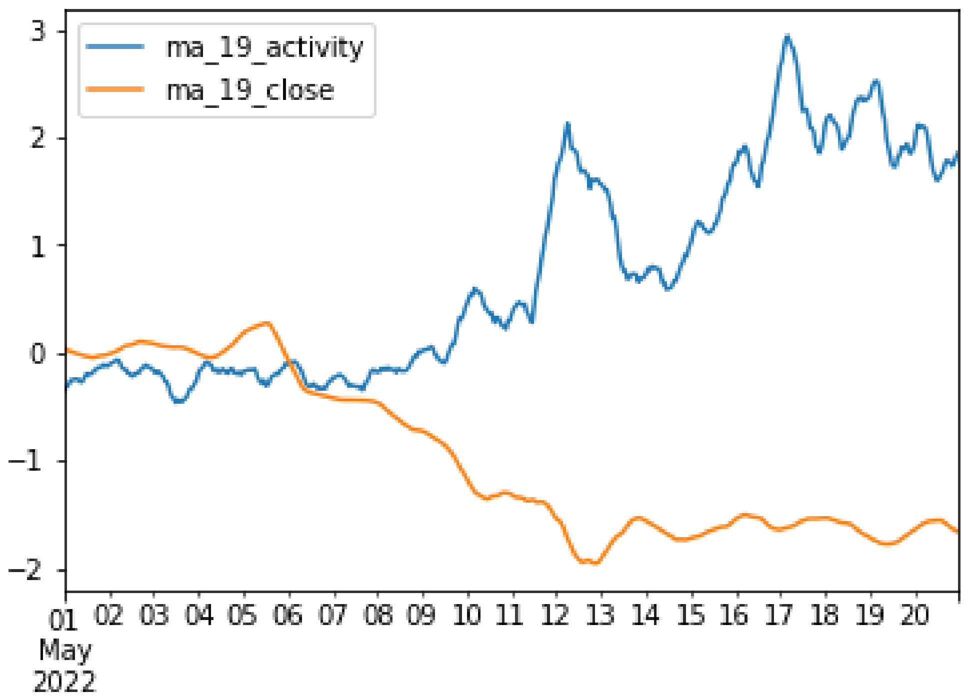
ma_19_activity
ma_15_close
3
2
1
0
−1
−2
01
May
2022
02
03
04
05
06
07
08
09
10
11
12
13
14
15
16
17
18
19
20

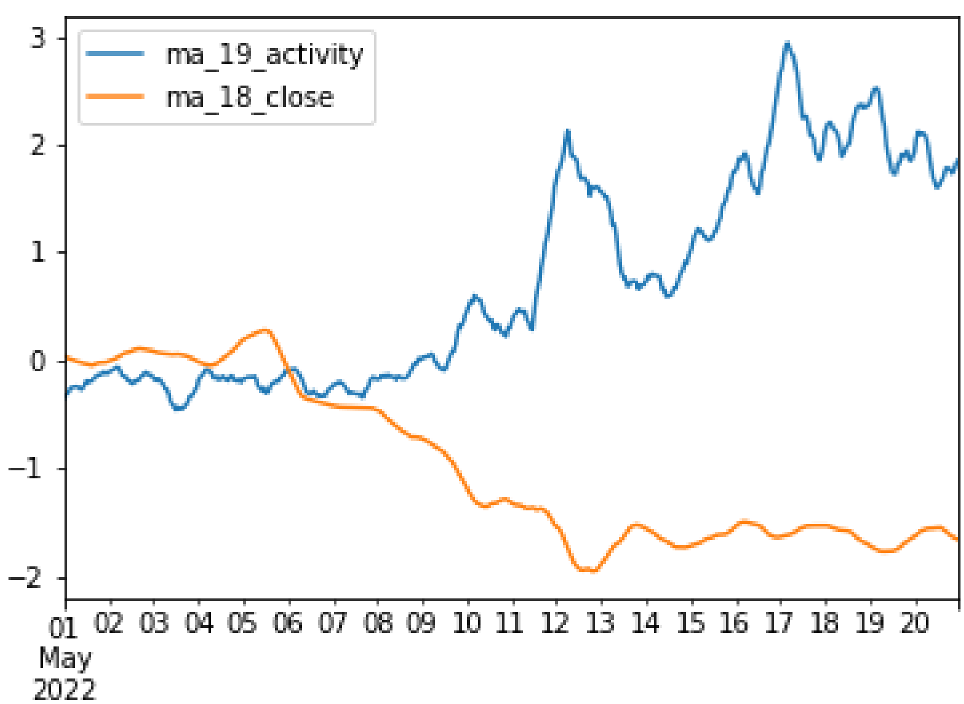


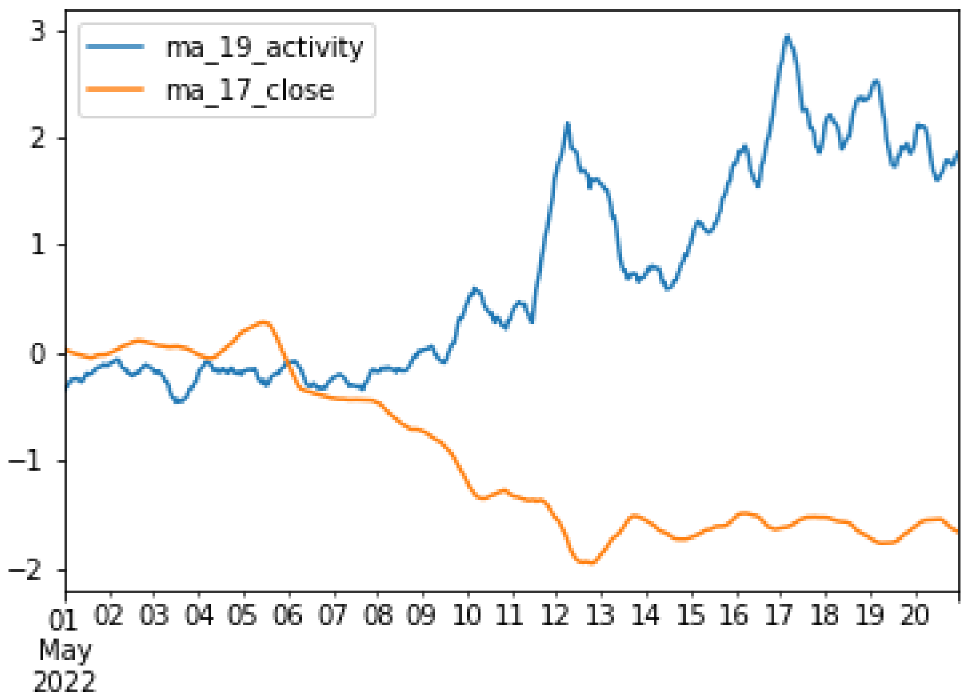
Let's do the same for pearson

[312]:
```
d = joined_data[fr:to]
sp = compute_corr(d, pearson)
for i in range(3):
    s = sp[i]
    plot_corr(s)
    print(f"Correlation:\n{s[1]}")
```

```
Correlation:
[[ 1.         -0.84198055]
 [-0.84198055  1.        ]]
Correlation:
[[ 1.         -0.84144657]
 [-0.84144657  1.        ]]
Correlation:
[[ 1.        -0.8409315]
 [-0.8409315  1.       ]]
```


ma_19_activity
ma_19_close
3
2
1
0
−1
−2
01
May
2022
02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20


ma_19_activity
ma_18_close
3
2
1
0
−1
−2
01
May
2022
02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20



1.2 Try HSIC

[326]:
```
import numpy
from hsic import dHSIC


d = joined_data[fr:to]

r=[]
for p in ma_windows:
    for a in ma_windows:
        pair = [f'ma_{p}_activity',f'ma_{a}_close']
        j = d[pair].dropna().to_numpy().T

        x = np.array(j[0])
        y = np.array(j[1])

        v = dHSIC(x, y)
        r.append((v,c,pair))


sort = sorted(r, key=lambda tup: -tup[0])

fig, ax = plt.subplots(figsize=(12, 6))
```

```
print("HSIC:")
plt.plot(sort[0][1])
plt.savefig('plots/hisc.pdf')
print(f"Coefficient: {sort[0][0]}, pair: {sort[0][2]}")
```

```
HSIC:
Coefficient: 0.11296332474167503, pair: ['ma_19_activity', 'ma_19_close']
```