Data Analysis

November 22, 2020

[3]:
```python
import os
import math
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
%matplotlib inline
sns.set_style("whitegrid")
sns.set(rc={'figure.figsize':(10,8)})

import jpype
from jpype import JArray, JDouble, JInt
```

[4]:
```python
def validate_numpy_array(func):
    """ Convert any iterable to numpy array """
    def wrapper(*args, **kwargs):
        for item in args:
            try:
                # convert iterable to numpy array
                len(item)
                item = np.array(item)
            except TypeError as e:
                continue
        return func(*args, **kwargs)

    return wrapper

class ContinuousInfoEstimator:
    def __init__(self, jar_location=None, estimator='kraskov'):
        self.estimator = estimator

        if not jar_location:
            project_dir = 'Dropbox/Documents/Classes/InfoTheory'
            jidt_dir = os.path.join(os.environ['HOME'], project_dir)
            jar_location = os.path.join(jidt_dir, 'infodynamics-dist-1.5/
↪infodynamics.jar')
```

```python
        assert os.path.exists(jar_location), 'jar file not found: ' + jar_location

        # Start the JVM (add the "-Xmx" option with say 1024M if you get crashes due to not enough memory space)
        try:
            jpype.startJVM(jpype.getDefaultJVMPath(), "-ea", "-Djava.class.path=" + jar_location)

            # load package
            self.pkg = jpype.JPackage(f"infodynamics.measures.continuous.{estimator}")
            print('Estimator ready.')
        except OSError:
            print("Failed to start JVM. Check $JAVA_HOME environmental var.")

    def list_calculators(self):
        return [item for item in dir(self.pkg) if item[0].isupper() and item[0].isalpha()]

    @validate_numpy_array
    def transfer_entropy(self, src, dest, k=1, nearest_neighbors=4, normalize=True, auto_embed=False, compute_significance=False, n_samples=100):
        """ calculate transfer entropy in nats. """
        src = np.array(src)
        dest = np.array(dest)

        assert len(src) == len(dest), f'Length mismatch: {len(src)}, {len(dest)}'

        if self.estimator == 'gaussian':
            calc = self.pkg.TransferEntropyCalculatorGaussian()
        elif self.estimator == 'kraskov':
            calc = self.pkg.TransferEntropyCalculatorKraskov()

            if auto_embed:
                calc.setProperty("AUTO_EMBED_METHOD", "MAX_CORR_AIS_DEST_ONLY")
            else:
                normalize_var = 'true' if normalize else 'false'
                calc.setProperty("NORMALISE", normalize_var) # Normalise the individual variables
                calc.setProperty("k", f"{nearest_neighbors}") # Use Kraskov parameter K=4 for 4 nearest points

        calc.initialise(k) # Use history length k
```

```
        src_arr = JArray(JDouble, 1)(src.tolist())
        dest_arr = JArray(JDouble, 1)(dest.tolist())

        calc.setObservations(src_arr, dest_arr)

        if compute_significance:
            return calc.computeAverageLocalOfObservations(), calc.
↪computeSignificance(n_samples).pValue
        else:
            return calc.computeAverageLocalOfObservations()

    @validate_numpy_array
    def active_information_storage(self, arr, k=3):
        calc = self.pkg.ActiveInfoStorageCalculatorKraskov()

        # 2. Set any properties to non-default values:
        calc.setProperty("k_HISTORY", f"{k}")
        calc.initialise()
        calc.setObservations(arr)
        return calc.computeAverageLocalOfObservations()

# utility functions
def pct_change(df):
    return (df['adj_close'] - df['adj_close'].shift(1)) / df['adj_close'].
↪shift(1)

def daily_return(df):
    return np.log(df['adj_close']) - np.log(df['adj_close'].shift(1))

def compute_std(df):
    return np.sqrt(np.sum((df['daily_return'] - df['daily_return'].mean()) **␣
↪2) / (len(df) - 1))
```

[5]:
```
estimator = 'kraskov'
```

[6]:
```
try:
    options = calc.list_calculators()
except NameError:
    calc = ContinuousInfoEstimator(estimator=estimator)
    options = calc.list_calculators()

for item in options:
    print(item)
```

```
Estimator ready.
ActiveInfoStorageCalculatorKraskov
```

```
ActiveInfoStorageCalculatorMultiVariateKraskov
ConditionalMutualInfoCalculatorMultiVariateKraskov
ConditionalMutualInfoCalculatorMultiVariateKraskov1
ConditionalMutualInfoCalculatorMultiVariateKraskov2
ConditionalTransferEntropyCalculatorKraskov
MultiInfoCalculatorKraskov
MultiInfoCalculatorKraskov1
MultiInfoCalculatorKraskov2
MutualInfoCalculatorMultiVariateKraskov
MutualInfoCalculatorMultiVariateKraskov1
MutualInfoCalculatorMultiVariateKraskov2
PredictiveInfoCalculatorKraskov
TransferEntropyCalculatorKraskov
TransferEntropyCalculatorMultiVariateKraskov
```

1 Economy-level information transfer

1.1 Indices used

Index	Name	Country	n	Source
`^GSPC`	S&P 500	USA	500	Link
`^N100`	Euronext 100	Europe	100	Link
`^N225`	Nikkei 225	Japan	225	Link
`^BVSP`	Bovespa Index	Brazil	70	Link

- price expressed in local currency (USD, JPY, EUR, BRL)

1.2 External module used

https://github.com/gregversteeg/NPEET/blob/master/npeet/entropy_estimators.py

[7]:
```python
# code in this cell is borrowed from https://github.com/gregversteeg/NPEET/blob/
↪master/npeet/entropy_estimators.py
from scipy.special import digamma
from sklearn.neighbors import KDTree

def entropy(x, k=4, base=2):
    """ The classic K-L k-nearest neighbor continuous entropy estimator
        x should be a list of vectors, e.g. x = [[1.3], [3.7], [5.1], [2.4]]
        if x is a one-dimensional scalar and we have four samples
    """
    assert k <= len(x) - 1, "Set k smaller than num. samples - 1"
    x = np.asarray(x)
    n_elements, n_features = x.shape
    x = add_noise(x)
    tree = build_tree(x)
    nn = query_neighbors(tree, x, k)
```

```
    const = digamma(n_elements) - digamma(k) + n_features * np.log(2)
    return (const + n_features * np.log(nn).mean()) / np.log(base)

def add_noise(x, intens=1e-10):
    # small noise to break degeneracy, see doc.
    return x + intens * np.random.random_sample(x.shape)

def query_neighbors(tree, x, k):
    return tree.query(x, k=k + 1)[0][:, k]

def build_tree(points):
    if points.shape[1] >= 20:
        return BallTree(points, metric='chebyshev')
    return KDTree(points, metric='chebyshev')
```

2 Data preprocess

2.1 Read data

[8]:
```
dfs = {}
for file in os.listdir('data/index'):
    if file.startswith('^'):
        fn, ext = os.path.splitext(file)
        dfs[fn[1:]] = pd.read_csv(os.path.join('data/index', file))

dfs.keys()
```

[8]:
```
dict_keys(['N225', 'GSPC', 'N100', 'BVSP'])
```

[9]:
```
for df in dfs.values():
    df.columns = [col.lower().replace(' ', '_') for col in df.columns]
    df['date'] = pd.to_datetime(df['date'])
```

[10]:
```
for key in dfs.keys():
    print(key)
    print(dfs[key]['date'].describe(datetime_is_numeric=True))
    print('')
```

```
N225
count                          14356
mean     1992-08-16 21:16:48.080245120
min                1965-01-06 00:00:00
25%                1978-10-09 18:00:00
50%                1992-07-11 12:00:00
75%                2006-04-13 06:00:00
max                2020-10-29 00:00:00
Name: date, dtype: object
```

```
GSPC
count                            23317
mean     1974-07-03 11:10:15.259252912
min                1928-01-03 00:00:00
25%                1951-05-04 00:00:00
50%                1974-08-09 00:00:00
75%                1997-08-29 00:00:00
max                2020-10-28 00:00:00
Name: date, dtype: object

N100
count                             5357
mean     2010-05-17 12:58:27.933544960
min                2000-01-03 00:00:00
25%                2005-02-18 00:00:00
50%                2010-05-13 00:00:00
75%                2015-08-07 00:00:00
max                2020-10-30 00:00:00
Name: date, dtype: object

BVSP
count                             6984
mean     2006-11-27 21:07:50.103092992
min                1993-04-28 00:00:00
25%                2000-01-05 18:00:00
50%                2006-09-30 12:00:00
75%                2013-10-17 06:00:00
max                2020-10-28 00:00:00
Name: date, dtype: object
```

2.2 Compute Daily return

$$r_t = \ln p_t - \ln p_{t-1}$$

[11]:
```
for df in dfs.values():
    # df['pct_change'] = pct_change(df)
    df['daily_return'] = daily_return(df)
```

[12]:
```
dfs['GSPC'].head()
```

[12]:
```
        date       open       high        low      close  adj_close  volume  \
0 1928-01-03  17.760000  17.760000  17.760000  17.760000  17.760000       0
1 1928-01-04  17.719999  17.719999  17.719999  17.719999  17.719999       0
2 1928-01-05  17.549999  17.549999  17.549999  17.549999  17.549999       0
3 1928-01-06  17.660000  17.660000  17.660000  17.660000  17.660000       0
4 1928-01-09  17.500000  17.500000  17.500000  17.500000  17.500000       0
```

```
   daily_return
0           NaN
1     -0.002255
2     -0.009640
3      0.006248
4     -0.009101
```

2.3 Merge data

[13]:
```
from functools import reduce
cols = ['open', 'high', 'low', 'close', 'adj_close', 'volume']

for key in dfs.keys():
    dfs[key].rename(columns={'daily_return': key}, inplace=True)
    dfs[key].drop(cols, 1, inplace=True)

f = lambda left, right: pd.merge(left, right, on='date', how='inner')
data = reduce(f, dfs.values())
data.head()
```

[13]:
```
         date      N225      GSPC      N100      BVSP
0 2000-01-03       NaN -0.009595       NaN       NaN
1 2000-01-04       NaN -0.039099 -0.041794 -0.065855
2 2000-01-05 -0.024521  0.001920 -0.027262  0.024553
3 2000-01-06 -0.020391  0.000955 -0.008420 -0.008531
4 2000-01-07  0.001383  0.026730  0.022955  0.012463
```

[14]:
```
data.isnull().sum()
```

[14]:
```
date      0
N225    205
GSPC      0
N100     36
BVSP    143
dtype: int64
```

[15]:
```
data = data.fillna(method='ffill', limit=4)
data.head()
```

[15]:
```
         date      N225      GSPC      N100      BVSP
0 2000-01-03       NaN -0.009595       NaN       NaN
1 2000-01-04       NaN -0.039099 -0.041794 -0.065855
2 2000-01-05 -0.024521  0.001920 -0.027262  0.024553
3 2000-01-06 -0.020391  0.000955 -0.008420 -0.008531
4 2000-01-07  0.001383  0.026730  0.022955  0.012463
```

[16]:
```
data.isnull().sum()
```

[16]:
```
date     0
N225     6
GSPC     0
N100     1
BVSP     1
dtype: int64
```

[17]:
```
data.dropna(inplace=True)
```

3 Analysis

[18]:
```
data
```

[18]:

	date	N225	GSPC	N100	BVSP
2	2000-01-05	-0.024521	0.001920	-0.027262	0.024553
3	2000-01-06	-0.020391	0.000955	-0.008420	-0.008531
4	2000-01-07	0.001383	0.026730	0.022955	0.012463
5	2000-01-10	0.001383	0.011128	0.017163	0.042790
6	2000-01-11	0.001383	-0.013149	-0.006436	-0.026732
…	…	…	…	…	…
4886	2020-10-22	-0.007012	0.005205	-0.001982	0.013494
4887	2020-10-23	0.001801	0.003440	0.007600	-0.006477
4888	2020-10-26	-0.000947	-0.018764	-0.016265	-0.002403
4889	2020-10-27	-0.000364	-0.003030	-0.010426	-0.014066
4890	2020-10-28	-0.002869	-0.035926	-0.029471	-0.043469

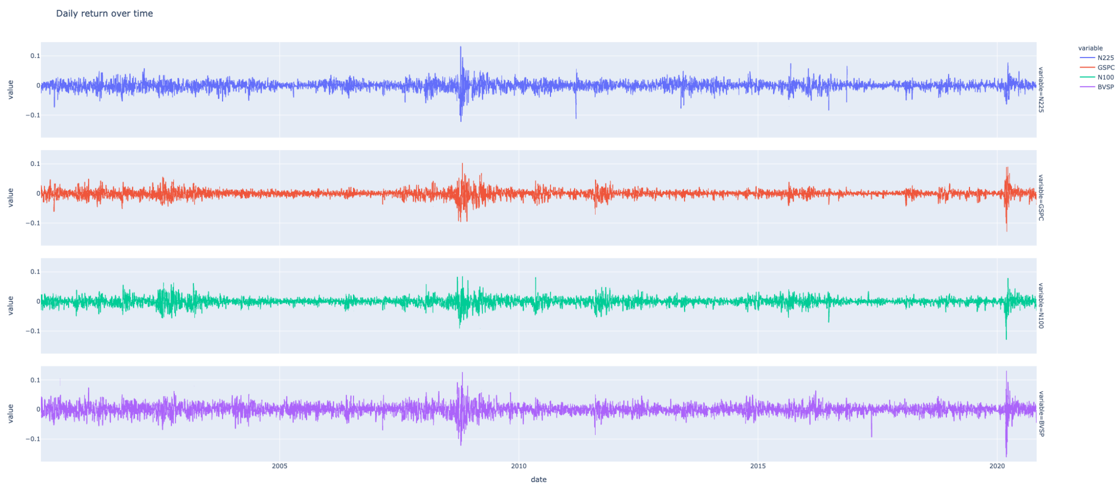
[4885 rows x 5 columns]

[19]:
```
data.describe()
```

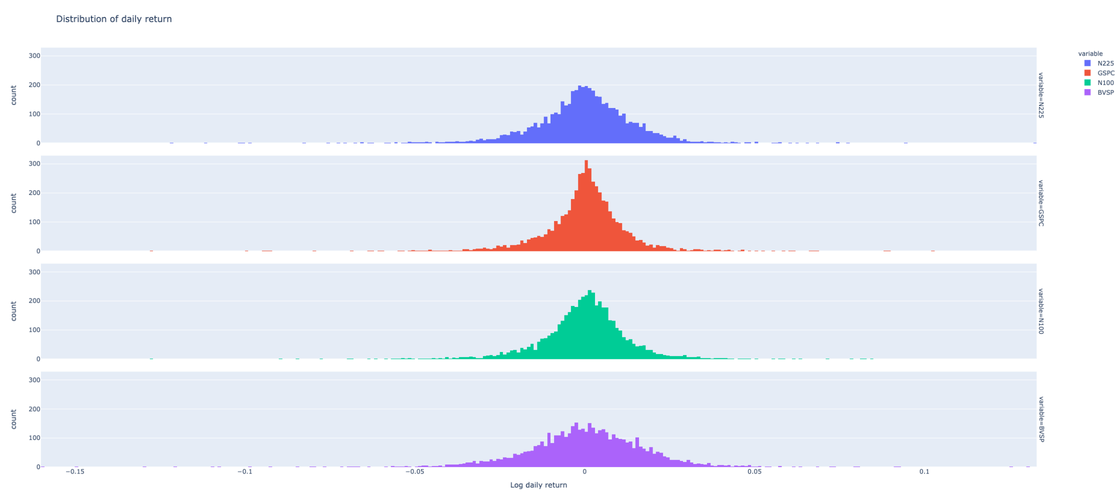
[19]:

	N225	GSPC	N100	BVSP
count	4885.000000	4885.000000	4885.000000	4885.000000
mean	-0.000054	0.000154	0.000019	0.000352
std	0.014694	0.012465	0.013142	0.017945
min	-0.121110	-0.127652	-0.127517	-0.159930
25%	-0.007039	-0.004813	-0.005979	-0.009430
50%	0.000278	0.000588	0.000604	0.000584
75%	0.007945	0.005805	0.006518	0.010869
max	0.132346	0.102457	0.084688	0.130223

[20]:
```
df = pd.melt(data, id_vars=['date'])
px.line(df, x='date', y='value', color='variable', facet_row='variable',␣
 ↪title='Daily return over time', height=1000, width=1000)
```




```
[55]: px.histogram(df, x='value', color='variable', facet_row='variable', width=1000,
      height=1000, title='Distribution of daily return', labels={'value': 'Log
      daily return'})
```



3.1 Shannon entropy

```
[22]: data.isnull().sum()
```

```
[22]: date    0
      N225    0
      GSPC    0
      N100    0
```

```
BVSP    0
dtype: int64
```

[23]:
```
data.dropna(inplace=True)
```

[24]:
```
print('entropy')
for col in data.columns:
    if col != 'date':
        h = entropy(data[col].dropna().values.reshape(-1, 1), base=math.e)
        print(f"{col} : {h:.2f}")
```

```
entropy
N225 : -3.01
GSPC : -3.12
N100 : -3.05
BVSP : -2.70
```

3.2 Transfer Entropy - USA and Japan

[25]:
```
select_data = data[['date', 'GSPC', 'N225']]
select_data = select_data[select_data['date'] < '2020-10-01']
```

[26]:
```
select_data['date'].describe(datetime_is_numeric=True)
```

[26]:
```
count                             4866
mean     2010-03-07 07:41:39.136868096
min                2000-01-05 00:00:00
25%                2004-11-10 06:00:00
50%                2010-01-28 12:00:00
75%                2015-06-17 18:00:00
max                2020-09-30 00:00:00
Name: date, dtype: object
```

[27]:
```
select_data.isnull().sum()
```

[27]:
```
date    0
GSPC    0
N225    0
dtype: int64
```

[28]:
```
calc.list_calculators()
```

[28]:
```
['ActiveInfoStorageCalculatorKraskov',
 'ActiveInfoStorageCalculatorMultiVariateKraskov',
 'ConditionalMutualInfoCalculatorMultiVariateKraskov',
 'ConditionalMutualInfoCalculatorMultiVariateKraskov1',
 'ConditionalMutualInfoCalculatorMultiVariateKraskov2',
```

```
 'ConditionalTransferEntropyCalculatorKraskov',
 'MultiInfoCalculatorKraskov',
 'MultiInfoCalculatorKraskov1',
 'MultiInfoCalculatorKraskov2',
 'MutualInfoCalculatorMultiVariateKraskov',
 'MutualInfoCalculatorMultiVariateKraskov1',
 'MutualInfoCalculatorMultiVariateKraskov2',
 'PredictiveInfoCalculatorKraskov',
 'TransferEntropyCalculatorKraskov',
 'TransferEntropyCalculatorMultiVariateKraskov']
```

3.2.1 Monthly

[29]:
```
cols = ['year', 'month', 't_GSPCtoN225', 't_N225toGSPC']
indices = ['GSPC', 'N225']
K = 4
monthly_stats = []

for yr in range(1993, 2021):
    for mm in range(1, 13):
        t_data = select_data[(select_data['date'].dt.year == yr) &␣
 ↪(select_data['date'].dt.month == mm)]
        if len(t_data) > K:
            row = [yr, mm]
            row += calc.transfer_entropy(src=t_data['GSPC'].values,␣
 ↪dest=t_data['N225'].values, k=1, nearest_neighbors=K),
            row += calc.transfer_entropy(src=t_data['N225'].values,␣
 ↪dest=t_data['GSPC'].values, k=1, nearest_neighbors=K),
            monthly_stats += row,

monthly = pd.DataFrame(monthly_stats, columns=cols)
monthly['yymmdd'] = monthly['year'].astype(str) + '-' + monthly['month'].
 ↪astype(str)
monthly['yymmdd'] = pd.to_datetime(monthly['yymmdd'])
monthly.head()
```

[29]:

	year	month	t_GSPCtoN225	t_N225toGSPC	yymmdd
0	2000	1	-0.012061	-0.059268	2000-01-01
1	2000	2	0.075308	-0.036129	2000-02-01
2	2000	3	-0.032728	-0.055256	2000-03-01
3	2000	4	0.118796	0.004676	2000-04-01
4	2000	5	0.175229	-0.031737	2000-05-01

[30]:
```
f = lambda x: max(0, x)
monthly['t_GSPCtoN225'] = monthly['t_GSPCtoN225'].apply(f)
monthly['t_N225toGSPC'] = monthly['t_N225toGSPC'].apply(f)
```

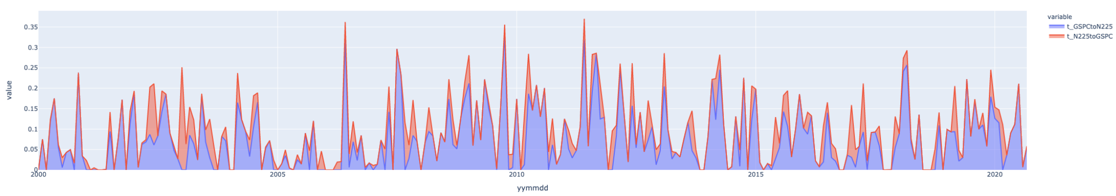
[31]:
```
monthly.describe()
```

[31]:

	year	month	t_GSPCtoN225	t_N225toGSPC
count	249.000000	249.000000	249.000000	249.000000
mean	2009.879518	6.445783	0.074649	0.022053
std	6.002817	3.442803	0.075162	0.035816
min	2000.000000	1.000000	0.000000	0.000000
25%	2005.000000	3.000000	0.006179	0.000000
50%	2010.000000	6.000000	0.057980	0.000000
75%	2015.000000	9.000000	0.115554	0.033758
max	2020.000000	12.000000	0.331706	0.251322

[32]:
```
# monthly.style.bar(subset=['t_GSPCtoN225', 't_N225toGSPC'], align='left',␣
↪color='#5fba7d')
```

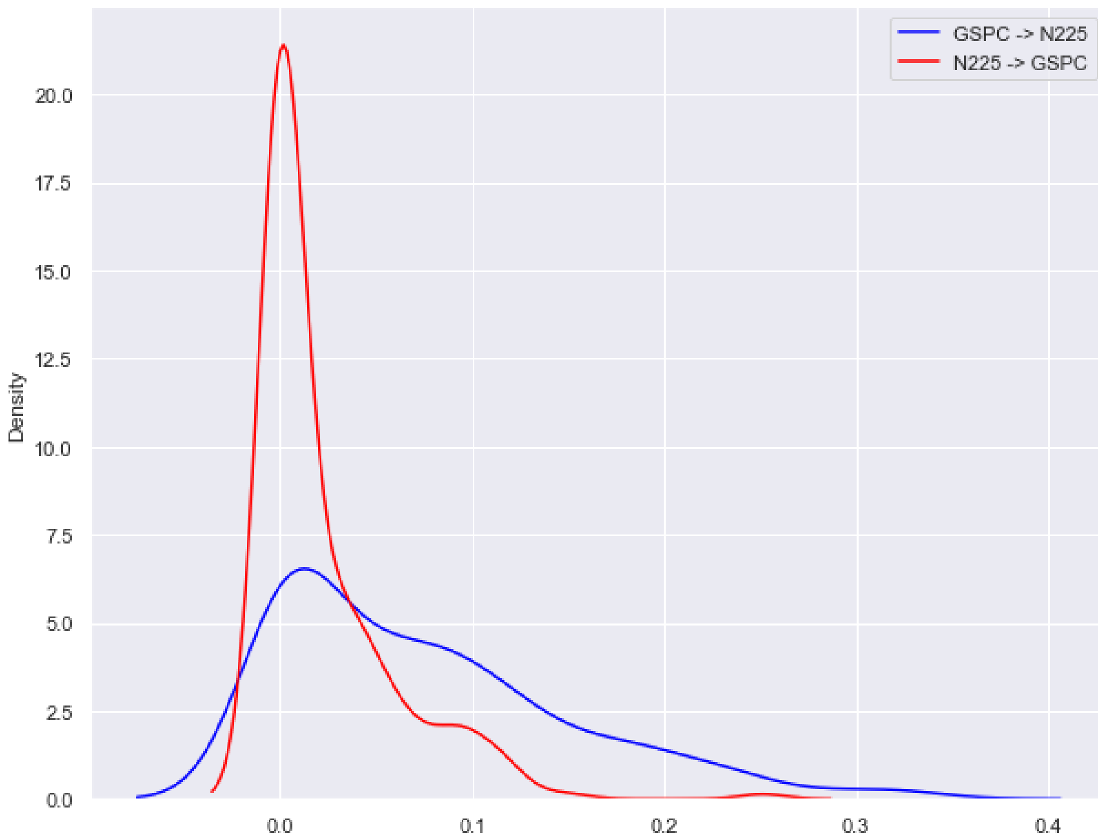
[33]:
```
# where red area is above blue area is where SPY has more influence on Nikkei␣
↪than the other way around
px.area(monthly, x='yymmdd', y=['t_GSPCtoN225', 't_N225toGSPC'])
```



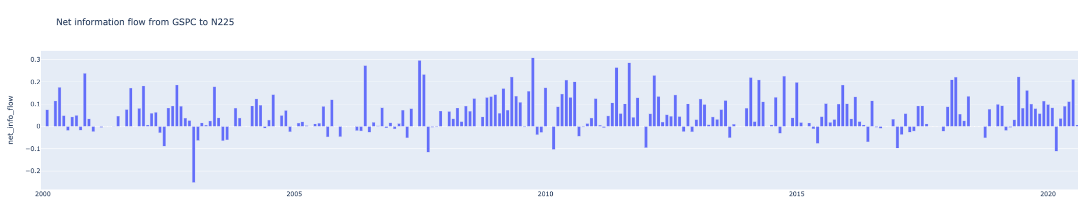
[34]:
```
# px.line(monthly, x='yymmdd', y=['t_GSPCtoN225', 't_N225toGSPC'])
```

[35]:
```
sns.kdeplot(monthly['t_GSPCtoN225'].values, color='blue', label='GSPC -> N225')
sns.kdeplot(monthly['t_N225toGSPC'].values, color='red', label='N225 -> GSPC')
plt.legend()
```

[35]:
```
<matplotlib.legend.Legend at 0x7f8b11746c10>
```



[36]:
```
f = lambda x: max(x, 0)
monthly['net_info_flow'] = monthly['t_GSPCtoN225'].apply(f) -␣
 ↪monthly['t_N225toGSPC'].apply(f)
px.bar(monthly, x='yymmdd', y='net_info_flow', title='Net information flow from␣
 ↪GSPC to N225')
```



[37]:
```
# net information flow from GSPC -> N225
# monthly[['year', 'month', 'net_info_flow']].style.
 ↪bar(subset=['net_info_flow'], align='mid', color=['#d65f5f', '#5fba7d'])
```

3.2.2 Yearly

[38]:
```
cols = ['year', 't_GSPCtoN225', 't_N225toGSPC']
indices = ['GSPC', 'N225']
K = 4
yearly_stats = []

for yr in range(1993, 2021):
    t_data = select_data[select_data['date'].dt.year == yr]
    if len(t_data) > K:
        row = [yr]
        row += calc.transfer_entropy(src=t_data['GSPC'].values,␣
 ↪dest=t_data['N225'].values, nearest_neighbors=K),
        row += calc.transfer_entropy(src=t_data['N225'].values,␣
 ↪dest=t_data['GSPC'].values, nearest_neighbors=K),
        yearly_stats += row,

yearly = pd.DataFrame(yearly_stats, columns=cols)
yearly['yymmdd'] = yearly['year'].astype(str) + '-01-01'
yearly['yymmdd'] = pd.to_datetime(yearly['yymmdd'])
f = lambda x: max(0, x)
yearly['t_GSPCtoN225'] = yearly['t_GSPCtoN225'].apply(f)
yearly['t_N225toGSPC'] = yearly['t_N225toGSPC'].apply(f)
```

[38]:

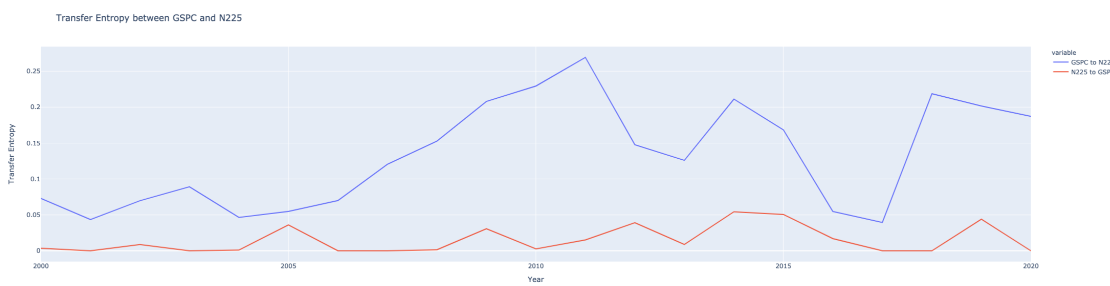
	year	t_GSPCtoN225	t_N225toGSPC	yymmdd
0	2000	0.072982	0.003568	2000-01-01
1	2001	0.043448	0.000000	2001-01-01
2	2002	0.069751	0.008767	2002-01-01
3	2003	0.089150	0.000000	2003-01-01
4	2004	0.046556	0.000993	2004-01-01
5	2005	0.054815	0.036079	2005-01-01
6	2006	0.069950	0.000000	2006-01-01
7	2007	0.120493	0.000000	2007-01-01
8	2008	0.152673	0.001503	2008-01-01
9	2009	0.207931	0.030833	2009-01-01
10	2010	0.229401	0.002642	2010-01-01
11	2011	0.269289	0.015190	2011-01-01
12	2012	0.147744	0.039211	2012-01-01
13	2013	0.125985	0.008871	2013-01-01
14	2014	0.211213	0.054382	2014-01-01
15	2015	0.168373	0.050655	2015-01-01
16	2016	0.054729	0.016947	2016-01-01
17	2017	0.039395	0.000000	2017-01-01
18	2018	0.218760	0.000000	2018-01-01
19	2019	0.201544	0.044058	2019-01-01
20	2020	0.187151	0.000000	2020-01-01

[44]:
```python
yearly.describe()
```

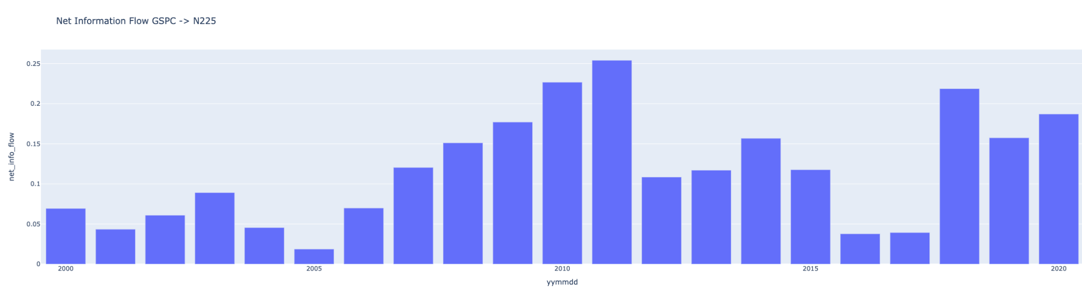
[44]:

	year	t_GSPCtoN225	t_N225toGSPC
count	21.000000	21.000000	21.000000
mean	2010.000000	0.132444	0.014938
std	6.204837	0.073019	0.019059
min	2000.000000	0.039395	0.000000
25%	2005.000000	0.069751	0.000000
50%	2010.000000	0.125985	0.003568
75%	2015.000000	0.201544	0.030833
max	2020.000000	0.269289	0.054382

[53]:
```python
px.line(yearly.rename(columns={'t_GSPCtoN225': 'GSPC to N225', 't_N225toGSPC': 'N225 to GSPC'}), x='year', y=['GSPC to N225', 'N225 to GSPC'], title='Transfer Entropy between GSPC and N225', width=1000, height=600, labels={'value':'Transfer Entropy', 'year':'Year'})
```



[46]:
```python
yearly['net_info_flow'] = yearly['t_GSPCtoN225'].apply(f) - yearly['t_N225toGSPC'].apply(f)
px.bar(yearly, x='yymmdd', y='net_info_flow', title='Net Information Flow GSPC -> N225', width=1000, height=600)
```



[52]:
```python
# net information flow from GSPC -> N225
```

```
yearly.drop('yymmdd', 1).rename(columns={'t_GSPCtoN225': 'GSPC to N225',␣
↪'t_N225toGSPC': 'N225 to GSPC'}).style.bar(subset=['GSPC to N225', 'N225 to␣
↪GSPC', 'net_info_flow'], align='mid', color=['#d65f5f', '#5fba7d'],␣
↪axis=None)
```

[52]: <pandas.io.formats.style.Styler at 0x7f8b126b7f10>

[48]:
```
print(yearly.drop('yymmdd', 1).to_markdown(index=False))
```

```
|   year |   t_GSPCtoN225 |   t_N225toGSPC |   net_info_flow |
|-------:|---------------:|---------------:|----------------:|
|   2000 |      0.0729822 |     0.00356808 |       0.0694141 |
|   2001 |      0.0434476 |     0          |       0.0434476 |
|   2002 |      0.069751  |     0.00876744 |       0.0609835 |
|   2003 |      0.0891499 |     0          |       0.0891499 |
|   2004 |      0.0465559 |     0.0009934  |       0.0455625 |
|   2005 |      0.0548151 |     0.0360793  |       0.0187358 |
|   2006 |      0.0699504 |     0          |       0.0699504 |
|   2007 |      0.120493  |     0          |       0.120493  |
|   2008 |      0.152673  |     0.00150333 |       0.15117   |
|   2009 |      0.207931  |     0.0308328  |       0.177098  |
|   2010 |      0.229401  |     0.00264219 |       0.226759  |
|   2011 |      0.269289  |     0.0151899  |       0.254099  |
|   2012 |      0.147744  |     0.0392109  |       0.108533  |
|   2013 |      0.125985  |     0.00887057 |       0.117115  |
|   2014 |      0.211213  |     0.0543823  |       0.156831  |
|   2015 |      0.168373  |     0.0506552  |       0.117718  |
|   2016 |      0.0547295 |     0.0169466  |       0.0377829 |
|   2017 |      0.0393947 |     0          |       0.0393947 |
|   2018 |      0.21876   |     0          |       0.21876   |
|   2019 |      0.201544  |     0.0440583  |       0.157486  |
|   2020 |      0.187151  |     0          |       0.187151  |
```

3.2.3 All periods + statistical significance

[41]:
```
k = 1
```

[56]:
```
USAtoJP, p1 = calc.transfer_entropy(src=select_data['GSPC'].values,␣
↪dest=select_data['N225'].values, nearest_neighbors=K,␣
↪compute_significance=True, n_samples=100)
print(USAtoJP, p1)
USAtoJP, p1 = calc.transfer_entropy(src=select_data['GSPC'].values,␣
↪dest=select_data['N225'].values, nearest_neighbors=K,␣
↪compute_significance=True, n_samples=100, k=7)
print(USAtoJP, p1)
```

```
0.13255940049378423 0.0
```

```
0.09599340794637734 0.0
```

[57]:
```
USAtoJP, p1 = calc.transfer_entropy(src=select_data['GSPC'].values,␣
↪dest=select_data['N225'].values, nearest_neighbors=K,␣
↪compute_significance=True, n_samples=100)
JPtoUSA, p2 = calc.transfer_entropy(src=select_data['N225'].values,␣
↪dest=select_data['GSPC'].values, nearest_neighbors=K,␣
↪compute_significance=True, n_samples=100)
print(USAtoJP, p1)
print(JPtoUSA, p2)
print(USAtoJP - JPtoUSA)
```

```
0.13265537558837215 0.0
0.01844362837195823 0.01
0.11421174721641392
```

[47]:
```
if p1 < 0.05 and p2 < 0.05:
    print('statistically significant')
else:
    print('not statistically significant')
```

```
statistically significant
```

3.3 Transfer Entropy - Japan and Brazil

[56]:
```
select_data = data[['date', 'N225', 'BVSP']]
select_data = select_data[select_data['date'] < '2020-10-01']
```

[57]:
```
cols = ['year', 't_N225toBVSP', 't_BVSPtoN225']
indices = ['N225', 'BVSP']
K = 4
yearly_stats = []

for yr in range(1993, 2021):
    t_data = select_data[select_data['date'].dt.year == yr]
    if len(t_data) > K:
        row = [yr]
        row += calc.transfer_entropy(src=t_data['N225'].values,␣
↪dest=t_data['BVSP'].values, nearest_neighbors=K),
        row += calc.transfer_entropy(src=t_data['BVSP'].values,␣
↪dest=t_data['N225'].values, nearest_neighbors=K),
        yearly_stats += row,

yearly = pd.DataFrame(yearly_stats, columns=cols)
yearly['yymmdd'] = yearly['year'].astype(str) + '-01-01'
yearly['yymmdd'] = pd.to_datetime(yearly['yymmdd'])
f = lambda x: max(0, x)
```

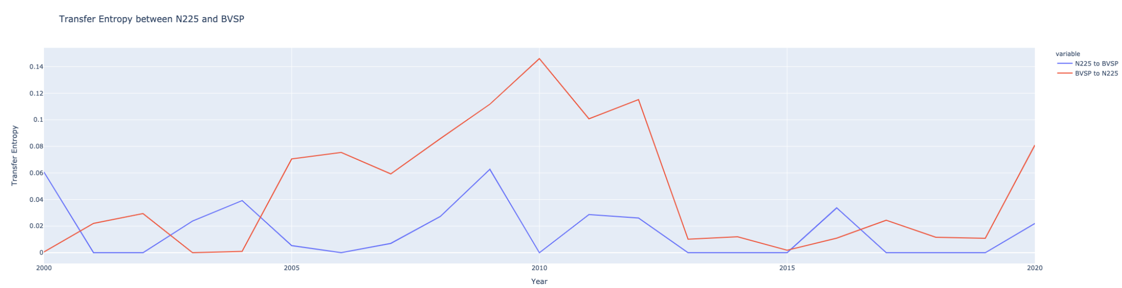
```
yearly['t_N225toBVSP'] = yearly['t_N225toBVSP'].apply(f)
yearly['t_BVSPtoN225'] = yearly['t_BVSPtoN225'].apply(f)
```

[58]:
```
yearly.describe()
```

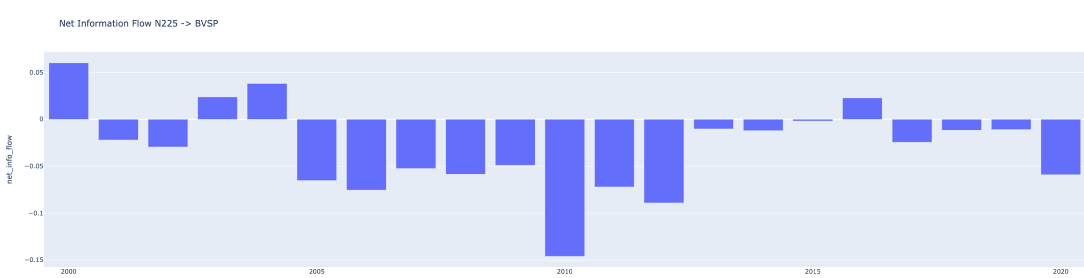
[58]:

	year	t_N225toBVSP	t_BVSPtoN225
count	21.000000	21.000000	21.000000
mean	2010.000000	0.016027	0.046686
std	6.204837	0.020345	0.045892
min	2000.000000	0.000000	0.000000
25%	2005.000000	0.000000	0.010862
50%	2010.000000	0.005340	0.024410
75%	2015.000000	0.027285	0.080967
max	2020.000000	0.062779	0.146024

[59]:
```
px.line(yearly.rename(columns={'t_N225toBVSP': 'N225 to BVSP', 't_BVSPtoN225':␣
↪'BVSP to N225'}), x='year', y=['N225 to BVSP', 'BVSP to N225'],␣
↪title='Transfer Entropy between N225 and BVSP', width=1000, height=600,␣
↪labels={'value':'Transfer Entropy', 'year':'Year'})
```



[60]:
```
yearly['net_info_flow'] = yearly['t_N225toBVSP'] - yearly['t_BVSPtoN225']
px.bar(yearly, x='yymmdd', y='net_info_flow', title='Net Information Flow N225␣
↪-> BVSP', width=1000, height=600)
```



[61]:
```python
# net information flow from N225 -> BVSP
yearly.drop('yymmdd', 1).rename(columns={'t_N225toBVSP': 'N225 to BVSP',␣
↪'t_BVSPtoN225': 'BVSP to N225'}).style.bar(subset=['N225 to BVSP', 'BVSP to␣
↪N225', 'net_info_flow'], align='mid', color=['#d65f5f', '#5fba7d'],␣
↪axis=None)
```

[61]: <pandas.io.formats.style.Styler at 0x7f8b129babd0>

3.3.1 All periods + statistical significance

[62]:
```python
k = 1
```

[63]:
```python
JPtoBVSP, p1 = calc.transfer_entropy(src=select_data['N225'].values,␣
↪dest=select_data['BVSP'].values, nearest_neighbors=K,␣
↪compute_significance=True, n_samples=100)
BVSPtoJP, p2 = calc.transfer_entropy(src=select_data['BVSP'].values,␣
↪dest=select_data['N225'].values, nearest_neighbors=K,␣
↪compute_significance=True, n_samples=100)
print(JPtoBVSP, p1)
print(BVSPtoJP, p2)
print(JPtoBVSP - BVSPtoJP)
```

```
0.009472571032241195 0.17
0.03597280447156126 0.0
-0.026500233439320064
```

[64]:
```python
if p1 < 0.05 and p2 < 0.05:
    print('statistically significant')
else:
    print('not statistically significant')
```

```
not statistically significant
```

3.4 Transfer Entropy Matrix / Contribution

[78]:
```python
data.isnull().sum()
```

[78]:
```
date    0
N225    0
GSPC    0
N100    0
BVSP    0
dtype: int64
```

[79]:
```python
data['date'].describe(datetime_is_numeric=True)
```

[79]:
```
count                               4885
mean       2010-03-22 09:22:08.720573184
min                  2000-01-05 00:00:00
25%                  2004-11-17 00:00:00
50%                  2010-02-12 00:00:00
75%                  2015-07-10 00:00:00
max                  2020-10-28 00:00:00
Name: date, dtype: object
```

[80]:
```
indices = [col for col in data.columns if col != 'date']
indices
```

[80]:
```
['N225', 'GSPC', 'N100', 'BVSP']
```

[81]:
```
all_transfer_entropy = np.zeros((len(indices), len(indices)))
all_transfer_entropy.shape
```

[81]:
```
(4, 4)
```

[82]:
```
for src_idx in range(len(indices)):
    for dest_idx in range(len(indices)):
        all_transfer_entropy[src_idx][dest_idx] = calc.
 ↪transfer_entropy(src=data[indices[src_idx]].values,                                                                          ␣
 ↪dest=data[indices[dest_idx]].values,                                                                          ␣
 ↪nearest_neighbors=K)
        all_transfer_entropy[src_idx][dest_idx] = max(0,␣
 ↪all_transfer_entropy[src_idx][dest_idx])
```

Row index -> source index

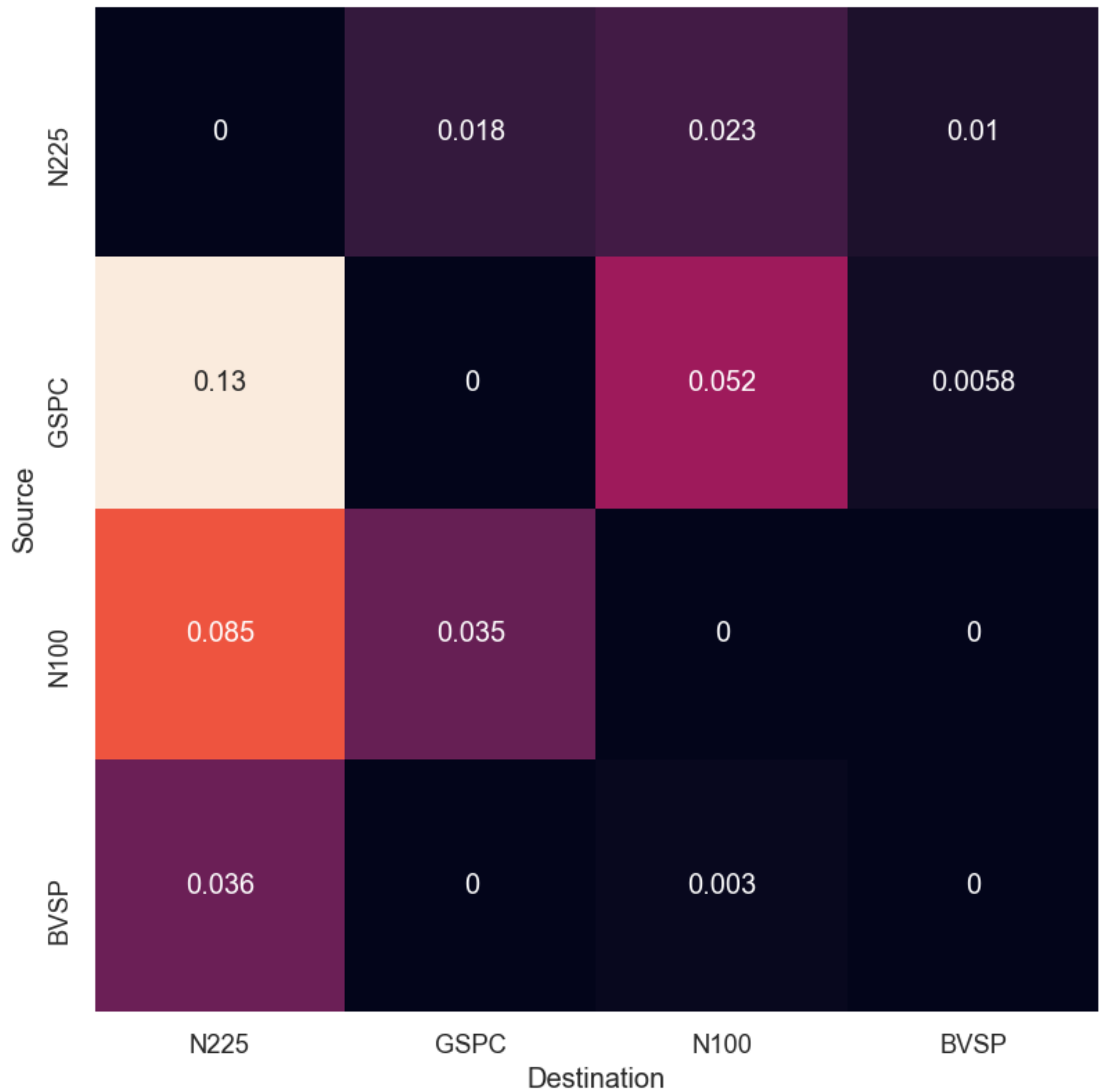
Column -> Destination index

[83]:
```
df = pd.DataFrame(all_transfer_entropy, columns=indices, index=indices)
df.style.background_gradient(axis=None)
```

[83]:
```
<pandas.io.formats.style.Styler at 0x7f8b12852ad0>
```

[84]:
```
plt.figure(figsize=(8,8), dpi=120)
sns.heatmap(df, annot=True, square=True, cbar=False)
plt.ylabel('Source')
plt.xlabel('Destination')
```

[84]:
```
Text(0.5, 79.5, 'Destination')
```



3.5 Total Transfer Entropy Contribution by Market

[85]:
```
# row wise summation = summation by source
te = df.values.sum(axis=1)
# normalize
te /= te.sum()

df = pd.DataFrame(np.stack([indices, te]).T, columns=['ETF',␣
↪'Transfer_entropy_contrib'])
df.rename(columns={'ETF':'index'}, inplace=True)
df.sort_values('Transfer_entropy_contrib', ascending=False, inplace=True)
df
```

[85]:
```
  index Transfer_entropy_contrib
1  GSPC        0.4741071138363235
2  N100       0.29966909312946194
0  N225        0.1278768951474355
3  BVSP       0.09834689788677912
```

[86]:
```
print(df.to_markdown(index=False))
```

```
| index    |   Transfer_entropy_contrib |
|:---------|---------------------------:|
| GSPC     |                  0.474107  |
| N100     |                  0.299669  |
| N225     |                  0.127877  |
| BVSP     |                  0.0983469 |
```

4 Industry-level information transfer

4.1 ETF used

Index	Name	Industry	Source
USO	United States Oil Fund	Oil	Link
ICLN	iShares Global Clean Energy ETF	Renewable Energy	Link
JETS	U.S. Global Jets ETF	Airline	Link
IYT	iShares Transportation Average ETF	Transportation	Link
XLP	Consumer Staples Select Sector SPDR Fund	Consumer staples	Link
SMH	VanEck Vectors Semiconductor ETF	Semiconductor	Link
IXP	iShares Global Comm Services ETF	Telecom	Link
VGT	Vanguard Information Technology Index Fund	Technology	Link
XPH	SPDR S&P Pharmaceuticals ETF	Pharmaceutical	Link

[87]:
```
industries = {
    'USO' : 'Oil',
    'ICLN': 'Renewable Energy',
    'JETS': 'Airline',
    'IYT' : 'Transportation',
    'XLP' : 'Consumer Staples',
    'SMH' : 'Semiconductor',
    'IXP' : 'Telecom',
    'VGT': 'Technology',
    'XPH' : 'Pharmaceutical'
}
```

4.2 Import data

[88]:
```
dfs = {}
path = 'data/etf'
for file in os.listdir(path):
    if file.endswith('csv'):
        fn, ext = os.path.splitext(file)
        dfs[fn] = pd.read_csv(os.path.join(path, file))

dfs.keys()
```

[88]:
```
dict_keys(['XPH', 'SMH', 'ICLN', 'JETS', 'XLP', 'USO', 'IXP', 'IYT', 'VGT'])
```

[89]:
```
for df in dfs.values():
    df.columns = [col.lower().replace(' ', '_') for col in df.columns]
    df['date'] = pd.to_datetime(df['date'])
```

[90]:
```
for key in dfs.keys():
    print(f"{key:>4} {dfs[key]['date'].dt.date.min()} {dfs[key]['date'].dt.date.
 ↪max()}")
```

```
 XPH 2006-07-03 2020-10-30
 SMH 2000-07-03 2020-10-30
ICLN 2008-07-01 2020-10-30
JETS 2015-05-01 2020-10-30
 XLP 1999-01-04 2020-10-30
 USO 2006-05-01 2020-10-30
 IXP 2001-12-03 2020-10-30
 IYT 2004-01-05 2020-10-30
 VGT 2004-02-02 2020-10-30
```

[91]:
```
for df in dfs.values():
    df['daily_return'] = daily_return(df)
```

[92]:
```
from functools import reduce
cols = ['open', 'high', 'low', 'close', 'adj_close', 'volume']

for key in dfs.keys():
    dfs[key].rename(columns={'daily_return': key}, inplace=True)
    dfs[key].drop(cols, 1, inplace=True)

f = lambda left, right: pd.merge(left, right, on='date', how='outer')
etf = reduce(f, dfs.values())
etf.head()
```

[92]:
```
        date  XPH       SMH  ICLN  JETS       XLP       USO       IXP  \
0 2006-07-03  NaN  0.012981   NaN   NaN  0.005771  0.002291  0.007590
1 2006-07-05  0.0 -0.027982   NaN   NaN -0.008254  0.015185 -0.007019
```

```
2 2006-07-06  0.0 -0.001762    NaN    NaN  0.011537 -0.003245  0.003610
3 2006-07-07  0.0 -0.016220    NaN    NaN -0.002050 -0.013085 -0.004753
4 2006-07-10  0.0 -0.022580    NaN    NaN  0.006138 -0.004160  0.002855

        IYT       VGT
0  0.011234  0.010543
1 -0.011911 -0.022512
2 -0.007147  0.002187
3 -0.008921 -0.012308
4  0.004471 -0.015377
```

[93]:
```
etf.isnull().sum()
```

[93]:
```
date       0
XPH     1886
SMH      379
ICLN    2388
JETS    4108
XLP        1
USO     1842
IXP      733
IYT     1258
VGT     1277
dtype: int64
```

4.3 Transfer Entropy of all pairs of indices

[94]:
```
cols = [col for col in etf.columns if col != 'date']
cols
```

[94]:
```
['XPH', 'SMH', 'ICLN', 'JETS', 'XLP', 'USO', 'IXP', 'IYT', 'VGT']
```

[95]:
```
all_transfer_entropy = np.zeros((len(cols), len(cols)))
all_transfer_entropy.shape
```

[95]:
```
(9, 9)
```

4.3.1 Use all of the available historical data for each index

[96]:
```
for src_idx in range(len(cols)):
    for dest_idx in range(len(cols)):
        if src_idx == dest_idx:
            continue

        src = etf[['date'] + [cols[src_idx]]]
        dest = etf[['date'] + [cols[dest_idx]]]
        merged = pd.merge(src, dest, on='date', how='inner').copy()
```

```
        merged.dropna(inplace=True)

        all_transfer_entropy[src_idx][dest_idx] = calc.
↪transfer_entropy(src=merged[cols[src_idx]].values,                          ␣
↪dest=merged[cols[dest_idx]].values,                                         ␣
↪nearest_neighbors=K)
        all_transfer_entropy[src_idx][dest_idx] = max(0,␣
↪all_transfer_entropy[src_idx][dest_idx])
```

[97]:
```
df = pd.DataFrame(all_transfer_entropy, columns=cols, index=cols)
df.style.background_gradient(axis=None)
```

[97]:
```
<pandas.io.formats.style.Styler at 0x7f8b1298f590>
```

[98]:
```
ticker_to_industry = lambda x: industries[x]
df.columns = [ticker_to_industry(ticker) for ticker in df.columns]
df.index = [ticker_to_industry(ticker) for ticker in df.index]
df.style.background_gradient(axis=None)
```

[98]:
```
<pandas.io.formats.style.Styler at 0x7f8b12852e10>
```

[99]:
```
# row wise summation = summation by source
te = df.values.sum(axis=1)
# normalize
te /= te.sum()

df = pd.DataFrame(np.stack([cols, te]).T, columns=['ETF',␣
↪'Transfer_entropy_contrib'])
df.sort_values('Transfer_entropy_contrib', ascending=False, inplace=True)
df['industry'] = df['ETF'].apply(lambda x: industries[x])
df
```

[99]:

	ETF	Transfer_entropy_contrib	industry
7	IYT	0.2229089063035986	Transportation
4	XLP	0.1422407073484226	Consumer Staples
2	ICLN	0.13639612259834097	Renewable Energy
8	VGT	0.11511357133209087	Technology
0	XPH	0.11480261503962244	Pharmaceutical
5	USO	0.08600950827792316	Oil
1	SMH	0.07132517041182107	Semiconductor
6	IXP	0.0641120836721178	Telecom
3	JETS	0.04709131501606252	Airline

4.3.2 Use the longest contiguous intersection of all ETF (2015-05-02 to 2020-10-31)

[100]:
```
for src_idx in range(len(cols)):
    for dest_idx in range(len(cols)):
        if src_idx == dest_idx:
            continue

        src = etf[['date'] + [cols[src_idx]]]
        dest = etf[['date'] + [cols[dest_idx]]]
        merged = pd.merge(src, dest, on='date', how='outer').copy()
        merged = merged[merged.date > '2015-05-02']

        all_transfer_entropy[src_idx][dest_idx] = calc.
 ↪transfer_entropy(src=merged[cols[src_idx]].values,
                                                                               ␣
 ↪dest=merged[cols[dest_idx]].values,
                                                                               ␣
 ↪nearest_neighbors=K)
        all_transfer_entropy[src_idx][dest_idx] = max(0,␣
 ↪all_transfer_entropy[src_idx][dest_idx])
```

[101]:
```
df = pd.DataFrame(all_transfer_entropy, columns=cols, index=cols)
df.style.background_gradient(axis=None)
```

[101]: <pandas.io.formats.style.Styler at 0x7f8af7a17090>

[102]:
```
ticker_to_industry = lambda x: industries[x]
df.columns = [ticker_to_industry(ticker) for ticker in df.columns]
df.index = [ticker_to_industry(ticker) for ticker in df.index]
df.style.background_gradient(axis=None)
```

[102]: <pandas.io.formats.style.Styler at 0x7f8af5642b50>

[103]:
```
# row wise summation = summation by source
te = df.values.sum(axis=1)
# normalize
te /= te.sum()

df = pd.DataFrame(np.stack([cols, te]).T, columns=['ETF',␣
 ↪'Transfer_entropy_contrib'])
df.sort_values('Transfer_entropy_contrib', ascending=False, inplace=True)
df['industry'] = df['ETF'].apply(lambda x: industries[x])
df
```

[103]:

	ETF	Transfer_entropy_contrib	industry
2	ICLN	0.23856391478416747	Renewable Energy
0	XPH	0.1437416568856891	Pharmaceutical

```
8    VGT      0.11927204357993224        Technology
6    IXP      0.11177475356069354           Telecom
5    USO      0.11154768415167443               Oil
4    XLP      0.09877226601577095   Consumer Staples
1    SMH      0.09037700748699166      Semiconductor
3   JETS      0.04896883693696498           Airline
7    IYT      0.03698183659811564     Transportation
```

4.4 Yearly transfer entropy contribution

[104]:
```
columns = ['Year'] + cols
columns
```

[104]:
```
['Year', 'XPH', 'SMH', 'ICLN', 'JETS', 'XLP', 'USO', 'IXP', 'IYT', 'VGT']
```

[105]:
```
etf['date'].describe(datetime_is_numeric=True)
```

[105]:
```
count                             5494
mean     2009-12-03 09:06:13.498361856
min                1999-01-04 00:00:00
25%                2004-06-22 06:00:00
50%                2009-12-02 12:00:00
75%                2015-05-19 18:00:00
max                2020-10-30 00:00:00
Name: date, dtype: object
```

[106]:
```
etf[etf['date'].dt.year == 2001]
```

[106]:

	date	XPH	SMH	ICLN	JETS	XLP	USO	IXP	IYT	VGT
3735	2001-01-02	NaN	-0.014388	NaN	NaN	-0.013216	NaN	NaN	NaN	NaN
3736	2001-01-03	NaN	0.152374	NaN	NaN	-0.047100	NaN	NaN	NaN	NaN
3737	2001-01-04	NaN	-0.031422	NaN	NaN	-0.040314	NaN	NaN	NaN	NaN
3738	2001-01-05	NaN	-0.061669	NaN	NaN	0.006632	NaN	NaN	NaN	NaN
3739	2001-01-08	NaN	0.014336	NaN	NaN	0.006588	NaN	NaN	NaN	NaN
…	…	…	…	…	…	…	…	…	…	…
3978	2001-12-24	NaN	-0.008629	NaN	NaN	-0.000389	NaN	0.000687	NaN	NaN
3979	2001-12-26	NaN	0.008867	NaN	NaN	0.002715	NaN	-0.002946	NaN	NaN
3980	2001-12-27	NaN	0.017268	NaN	NaN	-0.006216	NaN	0.012313	NaN	NaN
3981	2001-12-28	NaN	0.012353	NaN	NaN	-0.004296	NaN	0.005038	NaN	NaN
3982	2001-12-31	NaN	-0.031054	NaN	NaN	-0.005888	NaN	-0.001547	NaN	NaN

[248 rows x 10 columns]

[107]:
```
data = []
for year in range(2002, 2021):
    for src_idx in range(len(cols)):
        for dest_idx in range(len(cols)):
```

```
            if src_idx == dest_idx:
                continue

            logic = etf['date'].dt.year == year
            src = etf.loc[logic, ['date'] + [cols[src_idx]]]
            dest = etf.loc[logic, ['date'] + [cols[dest_idx]]]
            merged = pd.merge(src, dest, on='date', how='outer').copy()
            merged.dropna(inplace=True)
            if len(merged) > 180:
                all_transfer_entropy[src_idx][dest_idx] = calc.
↪transfer_entropy(src=merged[cols[src_idx]].values,
                                                                    ␣
↪dest=merged[cols[dest_idx]].values,
                                                                    ␣
↪nearest_neighbors=K)
                all_transfer_entropy[src_idx][dest_idx] = max(0,␣
↪all_transfer_entropy[src_idx][dest_idx])
            else:
                all_transfer_entropy[src_idx][dest_idx] = 0

    # row wise summation by source, and then normalize
    te = all_transfer_entropy.sum(axis=1)
    te /= te.sum()
    data += [year] + list(te),
```

[108]:
```
data = pd.DataFrame(data, columns=columns)
```

[109]:
```
data
```

[109]:

	Year	XPH	SMH	ICLN	JETS	XLP	USO	\
0	2002	0.000000	0.364597	0.000000	0.000000	0.539070	0.000000	
1	2003	0.000000	0.286339	0.000000	0.000000	0.484021	0.000000	
2	2004	0.000000	0.057432	0.000000	0.000000	0.128923	0.000000	
3	2005	0.000000	0.200727	0.000000	0.000000	0.111811	0.000000	
4	2006	0.000000	0.139536	0.000000	0.000000	0.244650	0.000000	
5	2007	0.022541	0.098821	0.000000	0.000000	0.039768	0.212414	
6	2008	0.206646	0.027069	0.000000	0.000000	0.046786	0.253242	
7	2009	0.025755	0.080795	0.067516	0.000000	0.239111	0.085411	
8	2010	0.073745	0.036852	0.160768	0.000000	0.005945	0.247680	
9	2011	0.152762	0.021780	0.002930	0.000000	0.245663	0.196458	
10	2012	0.106432	0.044908	0.127207	0.000000	0.035722	0.161529	
11	2013	0.155283	0.136378	0.136522	0.000000	0.108491	0.080565	
12	2014	0.157030	0.074150	0.174653	0.000000	0.017763	0.142595	
13	2015	0.134811	0.066876	0.121720	0.000000	0.081651	0.123798	
14	2016	0.029579	0.082583	0.204172	0.171032	0.095286	0.078596	
15	2017	0.044018	0.073447	0.089890	0.092513	0.127620	0.133536	
16	2018	0.085472	0.171393	0.018200	0.082158	0.115975	0.103253	

```
17  2019  0.105809  0.122708  0.091650  0.222176  0.105966  0.118576
18  2020  0.137132  0.132625  0.118430  0.019367  0.236226  0.023927

         IXP       IYT       VGT
0   0.096333  0.000000  0.000000
1   0.229640  0.000000  0.000000
2   0.253710  0.423001  0.136933
3   0.089557  0.357002  0.240904
4   0.226709  0.299499  0.089606
5   0.068317  0.280944  0.277195
6   0.200239  0.106582  0.159435
7   0.103912  0.254824  0.142676
8   0.270893  0.074315  0.129802
9   0.127701  0.065046  0.187659
10  0.155648  0.112169  0.256384
11  0.164030  0.122356  0.096376
12  0.144187  0.116789  0.172834
13  0.240952  0.119078  0.111114
14  0.169752  0.062957  0.106043
15  0.105533  0.231636  0.101807
16  0.194237  0.097198  0.132113
17  0.083357  0.057421  0.092337
18  0.156445  0.095328  0.080518
```

[110]:
```python
data.columns = [industries[col] if col != 'Year' else col for col in data.
 ↪columns]
data
```

[110]:
```
    Year  Pharmaceutical  Semiconductor  Renewable Energy   Airline  \
0   2002        0.000000       0.364597          0.000000  0.000000
1   2003        0.000000       0.286339          0.000000  0.000000
2   2004        0.000000       0.057432          0.000000  0.000000
3   2005        0.000000       0.200727          0.000000  0.000000
4   2006        0.000000       0.139536          0.000000  0.000000
5   2007        0.022541       0.098821          0.000000  0.000000
6   2008        0.206646       0.027069          0.000000  0.000000
7   2009        0.025755       0.080795          0.067516  0.000000
8   2010        0.073745       0.036852          0.160768  0.000000
9   2011        0.152762       0.021780          0.002930  0.000000
10  2012        0.106432       0.044908          0.127207  0.000000
11  2013        0.155283       0.136378          0.136522  0.000000
12  2014        0.157030       0.074150          0.174653  0.000000
13  2015        0.134811       0.066876          0.121720  0.000000
14  2016        0.029579       0.082583          0.204172  0.171032
15  2017        0.044018       0.073447          0.089890  0.092513
16  2018        0.085472       0.171393          0.018200  0.082158
17  2019        0.105809       0.122708          0.091650  0.222176
```

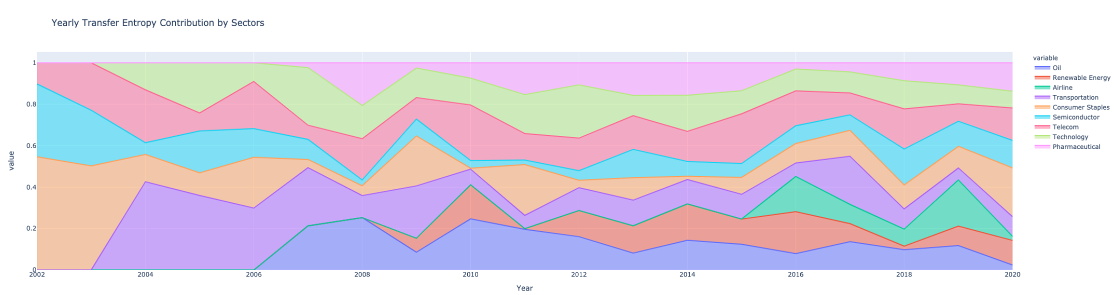
18	2020	0.137132	0.132625	0.118430	0.019367

	Consumer Staples	Oil	Telecom	Transportation	Technology
0	0.539070	0.000000	0.096333	0.000000	0.000000
1	0.484021	0.000000	0.229640	0.000000	0.000000
2	0.128923	0.000000	0.253710	0.423001	0.136933
3	0.111811	0.000000	0.089557	0.357002	0.240904
4	0.244650	0.000000	0.226709	0.299499	0.089606
5	0.039768	0.212414	0.068317	0.280944	0.277195
6	0.046786	0.253242	0.200239	0.106582	0.159435
7	0.239111	0.085411	0.103912	0.254824	0.142676
8	0.005945	0.247680	0.270893	0.074315	0.129802
9	0.245663	0.196458	0.127701	0.065046	0.187659
10	0.035722	0.161529	0.155648	0.112169	0.256384
11	0.108491	0.080565	0.164030	0.122356	0.096376
12	0.017763	0.142595	0.144187	0.116789	0.172834
13	0.081651	0.123798	0.240952	0.119078	0.111114
14	0.095286	0.078596	0.169752	0.062957	0.106043
15	0.127620	0.133536	0.105533	0.231636	0.101807
16	0.115975	0.103253	0.194237	0.097198	0.132113
17	0.105966	0.118576	0.083357	0.057421	0.092337
18	0.236226	0.023927	0.156445	0.095328	0.080518

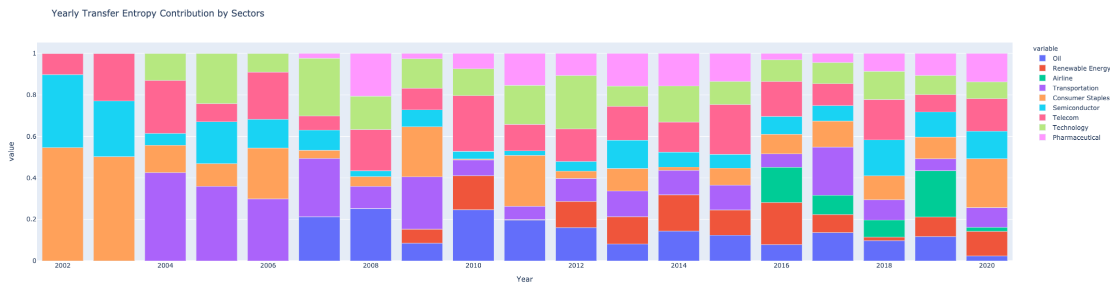
[117]:
```
data.style.background_gradient(axis=0, subset=list(industries.values()))
```

[117]: <pandas.io.formats.style.Styler at 0x7f8af7a3df90>

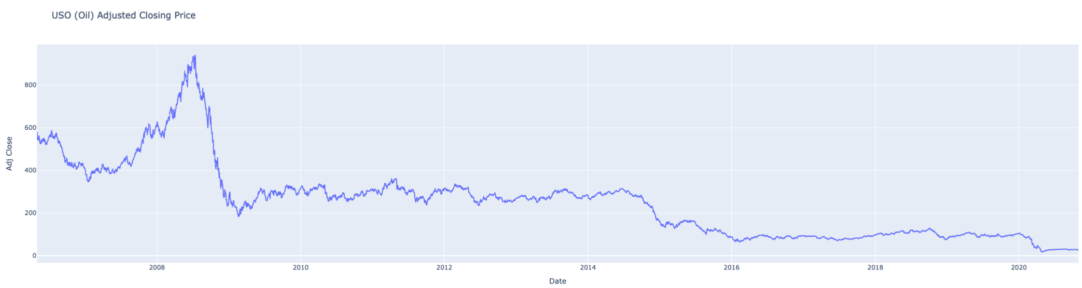
[72]:
```
px.area(data, x='Year', y=list(industries.values()), title='Yearly Transfer␣
↪Entropy Contribution by Sectors', width=1000, height=600)
```



[73]:
```
px.bar(data, x='Year', y=list(industries.values()), title='Yearly Transfer␣
↪Entropy Contribution by Sectors', width=1000, height=600)
```




```
[127]: df = pd.read_csv('data/etf/USO.csv')
       px.line(df, x='Date', y='Adj Close', width=1000, height=600, title='USO (Oil)␣
        ↪Adjusted Closing Price')
```



4.5 Net information flow between industries

4.5.1 Oil & Transportation

```
[73]: selected_ind = ['USO', 'IYT']
      cols = ['year', f'{selected_ind[0]}to{selected_ind[1]}',␣
       ↪f'{selected_ind[1]}to{selected_ind[0]}']
      K = 4
      yearly_stats = []

      for yr in range(2000, 2021):
          t_data = etf.loc[etf['date'].dt.year == yr, selected_ind].copy()
          t_data.dropna(inplace=True)
          if len(t_data) > K:
              row = [yr]
              row += calc.transfer_entropy(src=t_data[selected_ind[0]].values,␣
       ↪dest=t_data[selected_ind[1]].values, nearest_neighbors=K),
              row += calc.transfer_entropy(src=t_data[selected_ind[1]].values,␣
       ↪dest=t_data[selected_ind[0]].values, nearest_neighbors=K),
              yearly_stats += row,
```

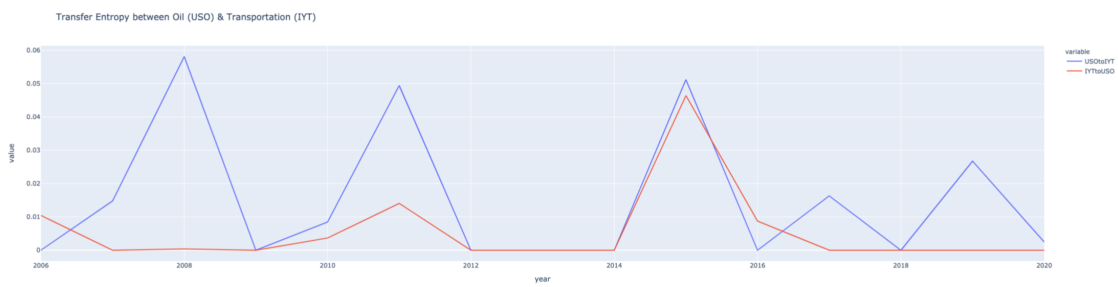
```
yearly = pd.DataFrame(yearly_stats, columns=cols)
f = lambda x: max(0, x)
yearly[cols[1]] = yearly[cols[1]].apply(f)
yearly[cols[2]] = yearly[cols[2]].apply(f)
yearly['net_info_flow'] = yearly[cols[1]] - yearly[cols[2]]
```

[74]:
```
yearly.describe()
```

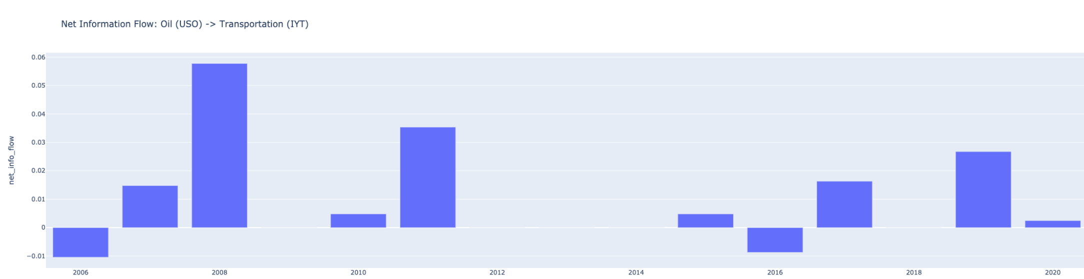
[74]:

	year	USOtoIYT	IYTtoUSO	net_info_flow
count	15.000000	15.000000	15.000000	15.000000
mean	2013.000000	0.015166	0.005575	0.009590
std	4.472136	0.021157	0.012192	0.018208
min	2006.000000	0.000000	0.000000	-0.010429
25%	2009.500000	0.000000	0.000000	0.000000
50%	2013.000000	0.002459	0.000000	0.002459
75%	2016.500000	0.021527	0.006197	0.015548
max	2020.000000	0.058124	0.046387	0.057743

[75]:
```
px.line(yearly, x='year', y=cols[1:], title=f'Transfer Entropy between␣
↪{industries[selected_ind[0]]} ({selected_ind[0]}) &␣
↪{industries[selected_ind[1]]} ({selected_ind[1]})', height=600, width=1000)
```



[76]:
```
px.bar(yearly, x='year', y='net_info_flow', title=f'Net Information Flow:␣
↪{industries[selected_ind[0]]} ({selected_ind[0]}) ->␣
↪{industries[selected_ind[1]]} ({selected_ind[1]})', height=600, width=1000)
```



```
[77]: print(f'Net Information Flow {selected_ind[0]} -> {selected_ind[1]}')
yearly.style.bar(subset=[col for col in yearly.columns if col != 'year'],␣
 ↪align='mid', color=['#d65f5f', '#5fba7d'], axis=None)
```

```
Net Information Flow USO -> IYT
```

```
[77]: <pandas.io.formats.style.Styler at 0x7fd488609bd0>
```

4.5.2 Oil & Renewable Energy

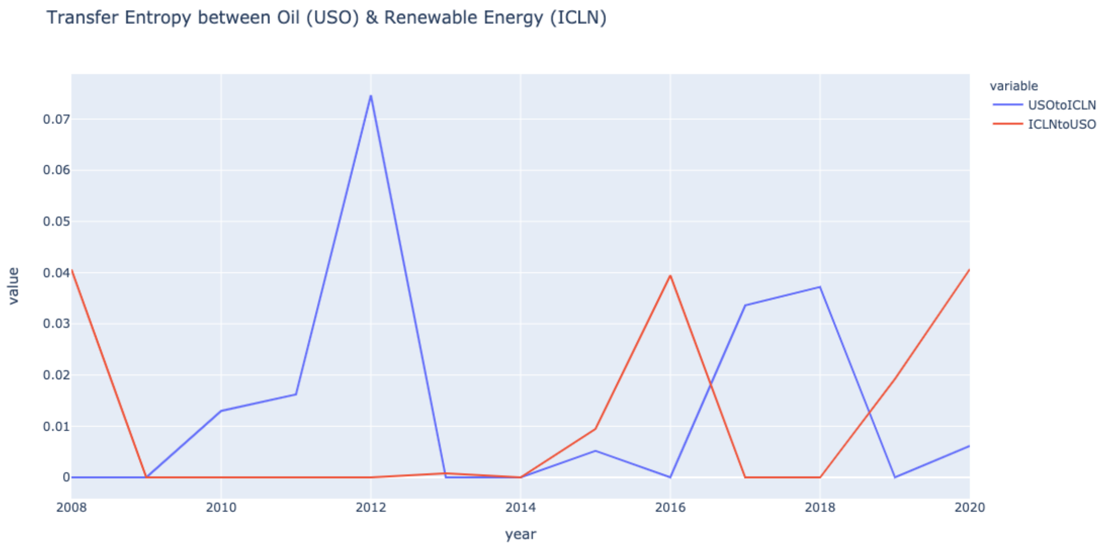
```
[78]: selected_ind = ['USO', 'ICLN']
cols = ['year', f'{selected_ind[0]}to{selected_ind[1]}',␣
 ↪f'{selected_ind[1]}to{selected_ind[0]}']
K = 4
yearly_stats = []

for yr in range(2000, 2021):
    t_data = etf.loc[etf['date'].dt.year == yr, selected_ind].copy()
    t_data.dropna(inplace=True)
    if len(t_data) > K:
        row = [yr]
        row += calc.transfer_entropy(src=t_data[selected_ind[0]].values,␣
 ↪dest=t_data[selected_ind[1]].values, nearest_neighbors=K),
        row += calc.transfer_entropy(src=t_data[selected_ind[1]].values,␣
 ↪dest=t_data[selected_ind[0]].values, nearest_neighbors=K),
        yearly_stats += row,

yearly = pd.DataFrame(yearly_stats, columns=cols)
f = lambda x: max(0, x)
yearly[cols[1]] = yearly[cols[1]].apply(f)
yearly[cols[2]] = yearly[cols[2]].apply(f)
yearly['net_info_flow'] = yearly[cols[1]] - yearly[cols[2]]
```

```
[79]: yearly.describe()
```

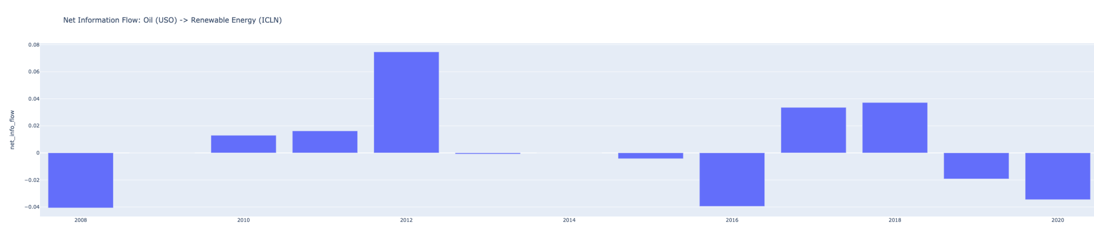
[79]:

	year	USOtoICLN	ICLNtoUSO	net_info_flow
count	13.00000	13.000000	13.000000	13.000000
mean	2014.00000	0.014307	0.011559	0.002747
std	3.89444	0.022215	0.017292	0.033181
min	2008.00000	0.000000	0.000000	-0.040631
25%	2011.00000	0.000000	0.000000	-0.019226
50%	2014.00000	0.005174	0.000000	0.000000
75%	2017.00000	0.016212	0.019226	0.016212
max	2020.00000	0.074654	0.040689	0.074654

[80]:
```python
px.line(yearly, x='year', y=cols[1:], title=f'Transfer Entropy between {industries[selected_ind[0]]} ({selected_ind[0]}) & {industries[selected_ind[1]]} ({selected_ind[1]})', height=600, width=1000)
```



[81]:
```python
px.bar(yearly, x='year', y='net_info_flow', title=f'Net Information Flow: {industries[selected_ind[0]]} ({selected_ind[0]}) -> {industries[selected_ind[1]]} ({selected_ind[1]})', height=600, width=1000)
```



[82]:
```python
print(f'Net Information Flow {selected_ind[0]} -> {selected_ind[1]}')
yearly.style.bar(subset=[col for col in yearly.columns if col != 'year'], align='mid', color=['#d65f5f', '#5fba7d'], axis=None)
```

```
Net Information Flow USO -> ICLN
```

[82]:
```
<pandas.io.formats.style.Styler at 0x7fd487a7da50>
```

4.5.3 Oil & Technology

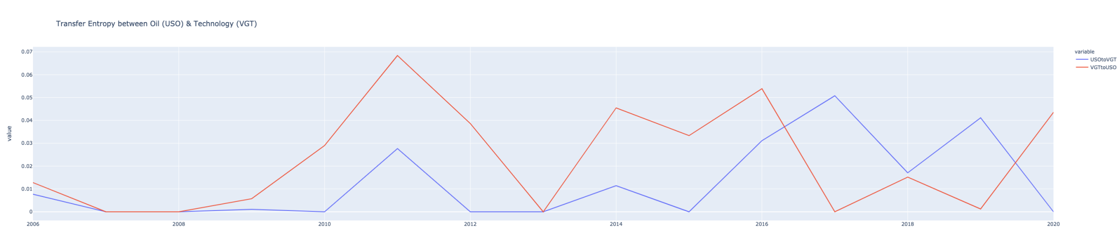
[83]:
```
selected_ind = ['USO', 'VGT']
cols = ['year', f'{selected_ind[0]}to{selected_ind[1]}',␣
↪f'{selected_ind[1]}to{selected_ind[0]}']
K = 4
yearly_stats = []

for yr in range(2000, 2021):
    t_data = etf.loc[etf['date'].dt.year == yr, selected_ind].copy()
    t_data.dropna(inplace=True)
    if len(t_data) > K:
        row = [yr]
        row += calc.transfer_entropy(src=t_data[selected_ind[0]].values,␣
↪dest=t_data[selected_ind[1]].values, nearest_neighbors=K),
        row += calc.transfer_entropy(src=t_data[selected_ind[1]].values,␣
↪dest=t_data[selected_ind[0]].values, nearest_neighbors=K),
        yearly_stats += row,

yearly = pd.DataFrame(yearly_stats, columns=cols)
f = lambda x: max(0, x)
yearly[cols[1]] = yearly[cols[1]].apply(f)
yearly[cols[2]] = yearly[cols[2]].apply(f)
yearly['net_info_flow'] = yearly[cols[1]] - yearly[cols[2]]
```

[84]:
```
yearly.describe()
```

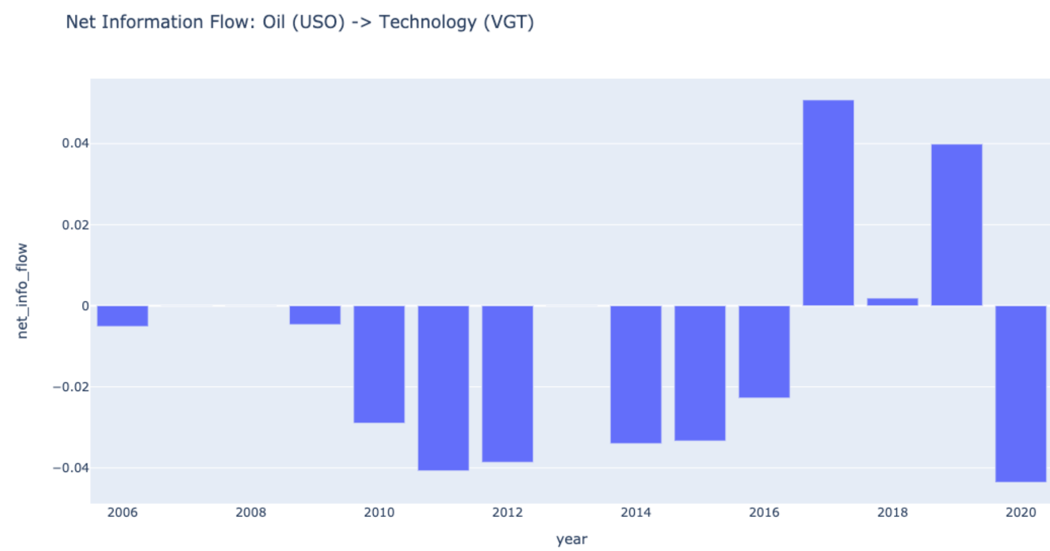
[84]:

	year	USOtoVGT	VGTtoUSO	net_info_flow
count	15.000000	15.000000	15.000000	15.000000
mean	2013.000000	0.012530	0.023137	-0.010608
std	4.472136	0.017175	0.022957	0.028284
min	2006.000000	0.000000	0.000000	-0.043547
25%	2009.500000	0.000000	0.000619	-0.033670
50%	2013.000000	0.001089	0.015165	-0.005103
75%	2016.500000	0.022359	0.041073	0.000000
max	2020.000000	0.050778	0.068384	0.050778

[85]:
```
px.line(yearly, x='year', y=cols[1:], title=f'Transfer Entropy between␣
↪{industries[selected_ind[0]]} ({selected_ind[0]}) &␣
↪{industries[selected_ind[1]]} ({selected_ind[1]})', height=600, width=1000)
```



[86]:
```
px.bar(yearly, x='year', y='net_info_flow', title=f'Net Information Flow:␣
↪{industries[selected_ind[0]]} ({selected_ind[0]}) ->␣
↪{industries[selected_ind[1]]} ({selected_ind[1]})', height=600, width=1000)
```



[87]:
```
print(f'Net Information Flow {selected_ind[0]} -> {selected_ind[1]}')
yearly.style.bar(subset=[col for col in yearly.columns if col != 'year'],␣
↪align='mid', color=['#d65f5f', '#5fba7d'], axis=None)
```

```
Net Information Flow USO -> VGT
```

[87]:
```
<pandas.io.formats.style.Styler at 0x7fd48762f890>
```

4.5.4 Semiconductor & Technology

[88]:
```
selected_ind = ['SMH', 'VGT']
cols = ['year', f'{selected_ind[0]}to{selected_ind[1]}',␣
↪f'{selected_ind[1]}to{selected_ind[0]}']
K = 4
yearly_stats = []

for yr in range(2000, 2021):
    t_data = etf.loc[etf['date'].dt.year == yr, selected_ind].copy()
    t_data.dropna(inplace=True)
    if len(t_data) > K:
        row = [yr]
```

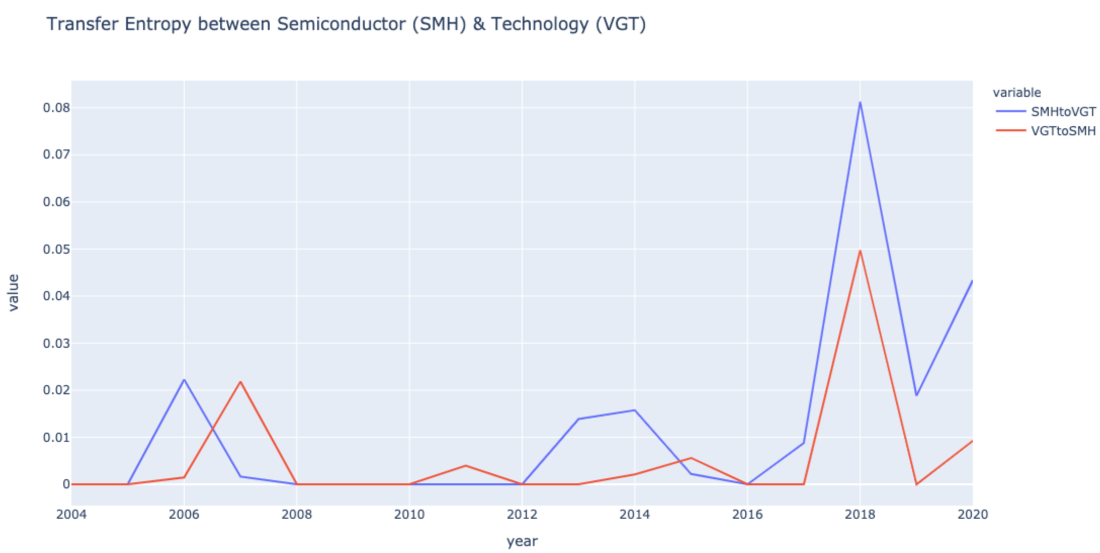
```
        row += calc.transfer_entropy(src=t_data[selected_ind[0]].values,␣
↪dest=t_data[selected_ind[1]].values, nearest_neighbors=K),
        row += calc.transfer_entropy(src=t_data[selected_ind[1]].values,␣
↪dest=t_data[selected_ind[0]].values, nearest_neighbors=K),
        yearly_stats += row,

yearly = pd.DataFrame(yearly_stats, columns=cols)
f = lambda x: max(0, x)
yearly[cols[1]] = yearly[cols[1]].apply(f)
yearly[cols[2]] = yearly[cols[2]].apply(f)
yearly['net_info_flow'] = yearly[cols[1]] - yearly[cols[2]]
```

[89]:
```
yearly.describe()
```

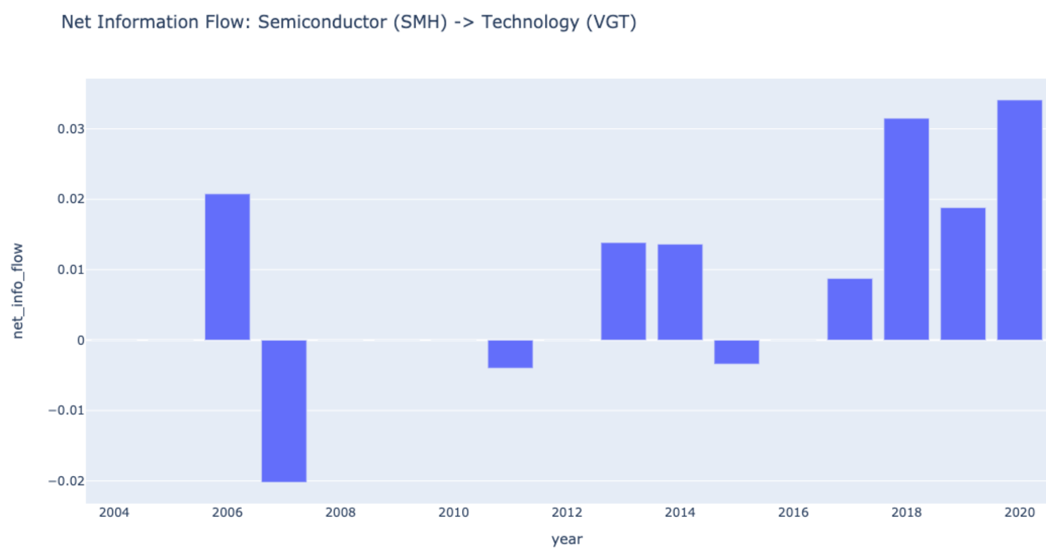
[89]:

	year	SMHtoVGT	VGTtoSMH	net_info_flow
count	17.000000	17.000000	17.000000	17.000000
mean	2012.000000	0.012225	0.005526	0.006698
std	5.049752	0.021376	0.012672	0.013850
min	2004.000000	0.000000	0.000000	-0.020193
25%	2008.000000	0.000000	0.000000	0.000000
50%	2012.000000	0.001628	0.000000	0.000000
75%	2016.000000	0.015738	0.003988	0.013852
max	2020.000000	0.081237	0.049729	0.034109

[90]:
```
px.line(yearly, x='year', y=cols[1:], title=f'Transfer Entropy between␣
↪{industries[selected_ind[0]]} ({selected_ind[0]}) &␣
↪{industries[selected_ind[1]]} ({selected_ind[1]})', height=600, width=1000)
```



```
[91]: px.bar(yearly, x='year', y='net_info_flow', title=f'Net Information Flow:␣
↪{industries[selected_ind[0]]} ({selected_ind[0]}) ->␣
↪{industries[selected_ind[1]]} ({selected_ind[1]})', height=600, width=1000)
```




```
[92]: print(f'Net Information Flow {selected_ind[0]} -> {selected_ind[1]}')
yearly.style.bar(subset=[col for col in yearly.columns if col != 'year'],␣
↪align='mid', color=['#d65f5f', '#5fba7d'], axis=None)
```

```
Net Information Flow SMH -> VGT
```

```
[92]: <pandas.io.formats.style.Styler at 0x7fd488289290>
```

4.5.5 Transportation & Renewable Energy

```
[93]: selected_ind = ['IYT', 'ICLN']
cols = ['year', f'{selected_ind[0]}to{selected_ind[1]}',␣
↪f'{selected_ind[1]}to{selected_ind[0]}']
K = 4
yearly_stats = []

for yr in range(2000, 2021):
    t_data = etf.loc[etf['date'].dt.year == yr, selected_ind].copy()
    t_data.dropna(inplace=True)
    if len(t_data) > K:
        row = [yr]
        row += calc.transfer_entropy(src=t_data[selected_ind[0]].values,␣
↪dest=t_data[selected_ind[1]].values, nearest_neighbors=K),
```

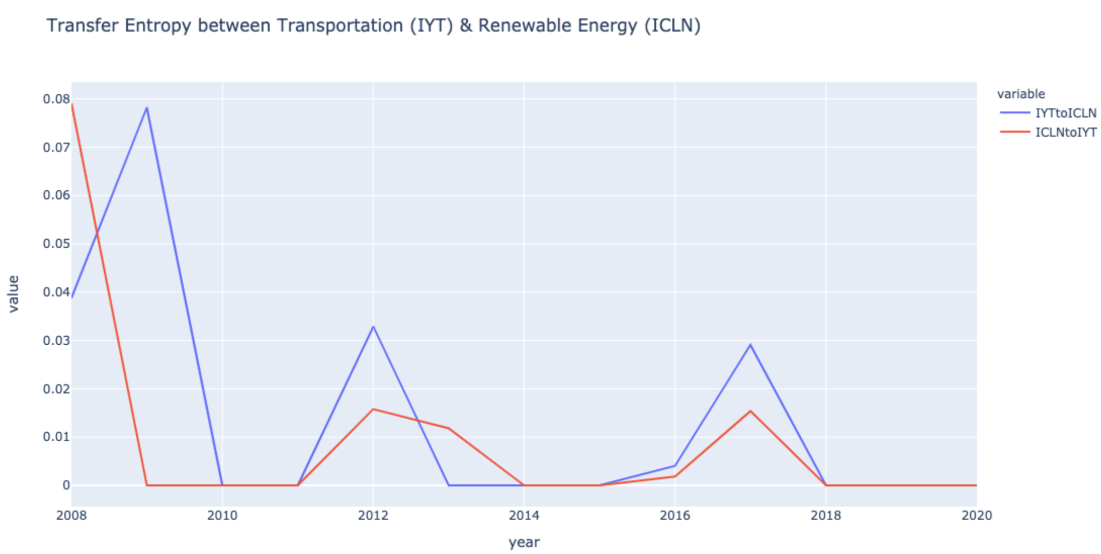
```
        row += calc.transfer_entropy(src=t_data[selected_ind[1]].values,␣
↪dest=t_data[selected_ind[0]].values, nearest_neighbors=K),
        yearly_stats += row,

yearly = pd.DataFrame(yearly_stats, columns=cols)
f = lambda x: max(0, x)
yearly[cols[1]] = yearly[cols[1]].apply(f)
yearly[cols[2]] = yearly[cols[2]].apply(f)
yearly['net_info_flow'] = yearly[cols[1]] - yearly[cols[2]]
```

[94]:
```
yearly.describe()
```

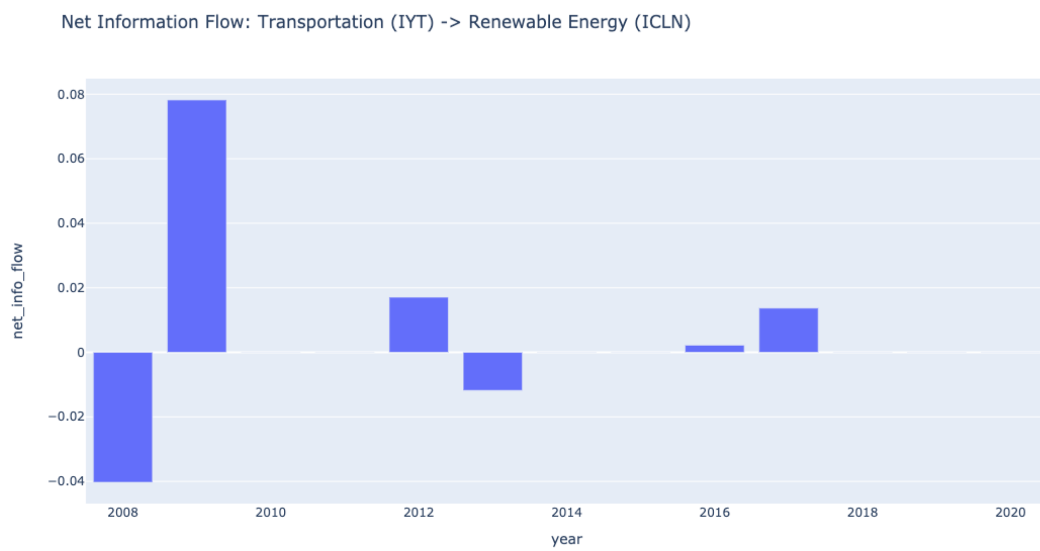
[94]:

	year	IYTtoICLN	ICLNtoIYT	net_info_flow
count	13.00000	13.000000	13.000000	13.000000
mean	2014.00000	0.014076	0.009527	0.004549
std	3.89444	0.024133	0.021796	0.025976
min	2008.00000	0.000000	0.000000	-0.040289
25%	2011.00000	0.000000	0.000000	0.000000
50%	2014.00000	0.000000	0.000000	0.000000
75%	2017.00000	0.029084	0.011814	0.002226
max	2020.00000	0.078221	0.079073	0.078221

[95]:
```
px.line(yearly, x='year', y=cols[1:], title=f'Transfer Entropy between␣
↪{industries[selected_ind[0]]} ({selected_ind[0]}) &␣
↪{industries[selected_ind[1]]} ({selected_ind[1]})', height=600, width=1000)
```



[96]:
```
px.bar(yearly, x='year', y='net_info_flow', title=f'Net Information Flow:␣
↪{industries[selected_ind[0]]} ({selected_ind[0]}) ->␣
↪{industries[selected_ind[1]]} ({selected_ind[1]})', width=1000, height=600)
```



[97]:
```
print(f'Net Information Flow {selected_ind[0]} -> {selected_ind[1]}')
yearly.style.bar(subset=[col for col in yearly.columns if col != 'year'],␣
↪align='mid', color=['#d65f5f', '#5fba7d'], axis=None)
```

```
Net Information Flow IYT -> ICLN
```

[97]: `<pandas.io.formats.style.Styler at 0x7fd487980e10>`

5 Company level information transfer

Index	Name	Industry	Source
XOM	ExxonMobil	Oil	Link
DAL	Delta Airline	Airline	Link

[5]:
```
delta = pd.read_csv('data/DAL.csv')
exxon = pd.read_csv('data/XOM.csv')
```

[6]:
```
for df in [delta, exxon]:
    df.columns = [col.lower().replace(' ', '_') for col in df.columns]
    df['date'] = pd.to_datetime(df['date'])
    df['daily_return'] = daily_return(df)
```

[7]:
```python
cols = ['date', 'daily_return']
df = pd.merge(delta[cols], exxon[cols], on='date', how='inner')
df = df.iloc[1:,:]
df.columns = ['date', 'Delta', 'Exxon']
df
```

[7]:
```
            date     Delta     Exxon
1     2007-05-07 -0.029997  0.003470
2     2007-05-08 -0.036514  0.006781
3     2007-05-09  0.008118  0.000491
4     2007-05-10 -0.004558 -0.020940
5     2007-05-11 -0.020514  0.022912
…          …        …        …
3394 2020-10-26 -0.062815 -0.023998
3395 2020-10-27 -0.038958 -0.016020
3396 2020-10-28 -0.035126 -0.038831
3397 2020-10-29  0.036753  0.043391
3398 2020-10-30 -0.003909 -0.010673

[3398 rows x 3 columns]
```

[8]:
```python
selected = ['Exxon', 'Delta']
cols = ['year', f'{selected[0]}To{selected[1]}',␣
 ↪f'{selected[1]}To{selected[0]}']
K = 4
yearly_stats = []

for yr in range(2007, 2021):
    t_data = df.loc[df['date'].dt.year == yr, selected].copy()
    t_data.dropna(inplace=True)
    if len(t_data) > K:
        row = [yr]
        row += calc.transfer_entropy(src=t_data[selected[0]].values,␣
 ↪dest=t_data[selected[1]].values, nearest_neighbors=K),
        row += calc.transfer_entropy(src=t_data[selected[1]].values,␣
 ↪dest=t_data[selected[0]].values, nearest_neighbors=K),
        yearly_stats += row,

yearly = pd.DataFrame(yearly_stats, columns=cols)
f = lambda x: max(0, x)
yearly[cols[1]] = yearly[cols[1]].apply(f)
yearly[cols[2]] = yearly[cols[2]].apply(f)
yearly['net_info_flow'] = yearly[cols[1]] - yearly[cols[2]]
```

[9]:
```python
print(f'Net Information Flow {selected[0]} -> {selected[1]}')
yearly.style.bar(subset=['net_info_flow'], align='mid', color=['#d65f5f',␣
 ↪'#5fba7d'])
```

```
Net Information Flow Exxon -> Delta
```

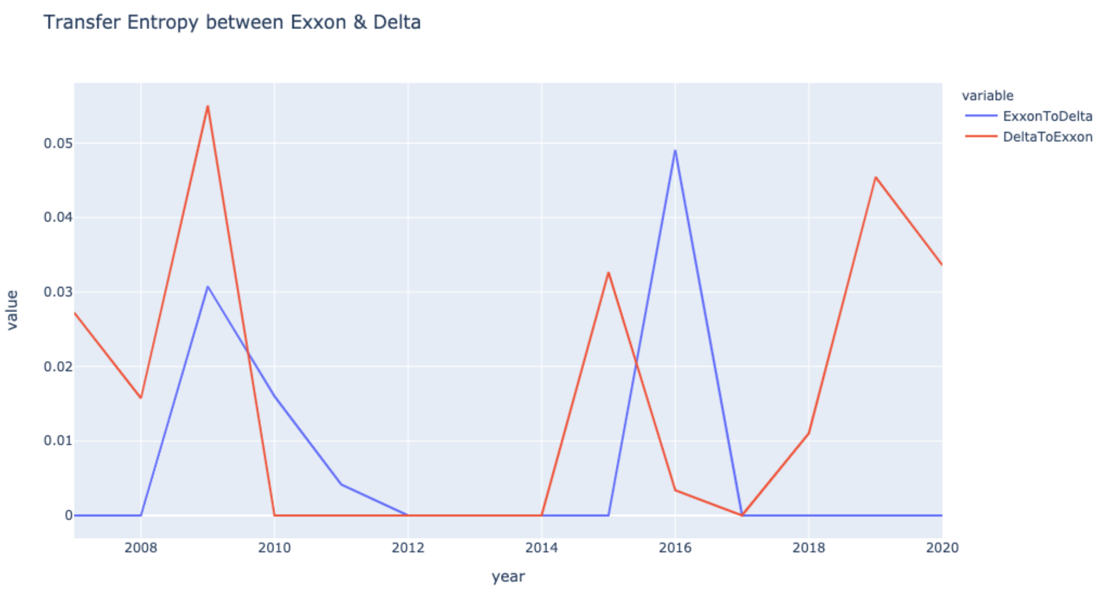
[9]: <pandas.io.formats.style.Styler at 0x7fd483e828d0>

[10]:
```python
print(f'Net Information Flow {selected[0]} -> {selected[1]}')
yearly.style.bar(subset=['net_info_flow'], align='mid', color=['#d65f5f',␣
↪'#5fba7d'])
```

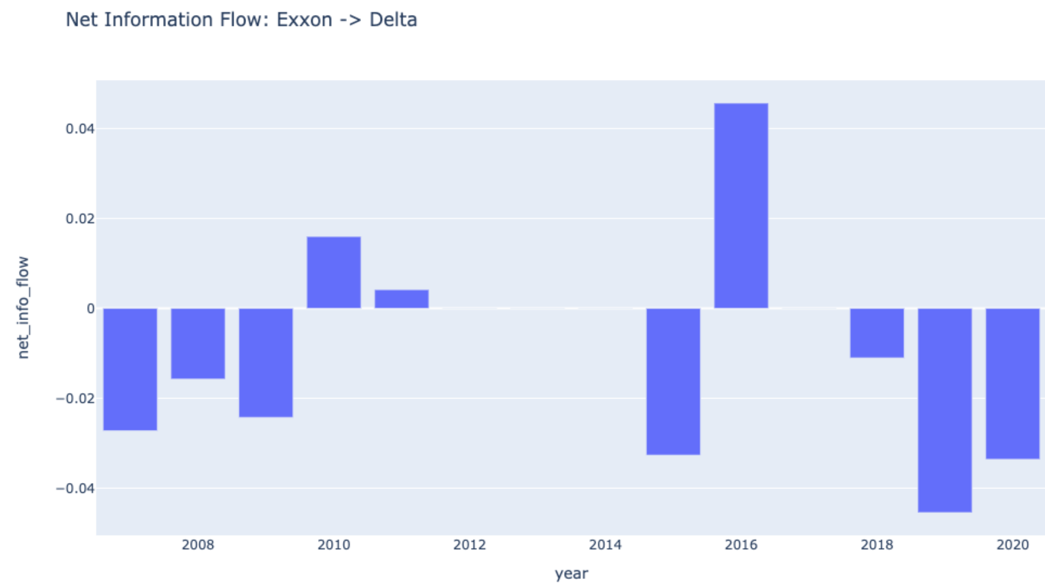
```
Net Information Flow Exxon -> Delta
```

[10]: <pandas.io.formats.style.Styler at 0x7fd4846b9d90>

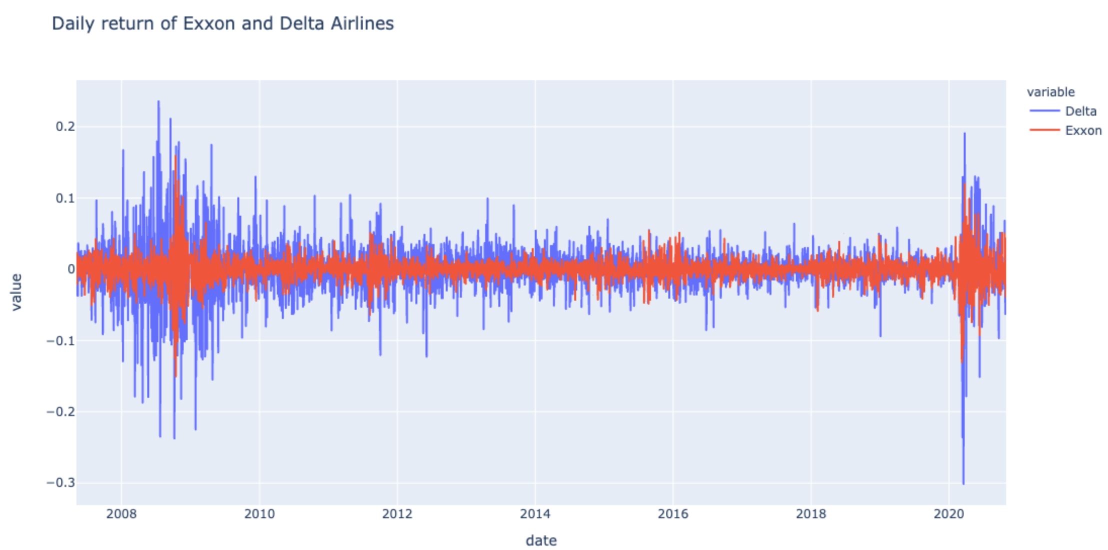
[11]:
```python
px.line(yearly, x='year', y=cols[1:], title=f'Transfer Entropy between␣
↪{selected[0]} & {selected[1]}', height=600, width=1000)
```



[12]:
```python
yearly['net_info_flow'] = yearly[cols[1]].apply(f) - yearly[cols[2]].apply(f)
px.bar(yearly, x='year', y='net_info_flow', title=f'Net Information Flow:␣
↪{selected[0]} -> {selected[1]}', width=1000, height=600)
```



[13]:
```
px.line(df, x='date', y=['Delta', 'Exxon'], title='Daily return of Exxon and␣
↪Delta Airlines', width=1000, height=600)
```



Articles on Exxon Mobil from 2016: Link

[ ]:
```

```