

# Dynamic Network Analysis 00

July 14, 2016

## 1 Table of Contents

- 1 Introduction
  - 1.1 Dynamic Network Analysis of Enron Email Network Data
  - 1.2 Data Preprocessing
  - 1.3 Key Assumption
- 2 Import Libraries
- 3 Import Data
- 4 Data Partition
  - 4.1 Break data into years
  - 4.2 Create networks at different timesteps
    - 4.2.1  $t = 0$
    - 4.2.2  $t = 1$
    - 4.2.3  $t = 2$
    - 4.2.4  $t = 3$
    - 4.2.5  $t = 4$
    - 4.2.6  $t = 5$
- 5 Network Statistics
  - 5.1 Centrality analysis without averaging
    - 5.1.1 Calculate all centralities in one go
    - 5.1.2 Degree Centrality
    - 5.1.3 Eigenvector Centrality Histograms
    - 5.1.4 Closeness Centrality Histograms
    - 5.1.5 Betweenness Centrality Histogram
    - 5.1.6 Communicability Centrality Histograms
    - 5.1.7 Katz Centrality Histograms
    - 5.1.8 Load Centrality
  - 5.2 Centrality Analysis with averaging
    - 5.2.1 Calculate Centrality Statistics at different time steps
- 6 Assortativity Analysis
  - 6.1 Calculate Assortativity statistics for each time step
- 7 Graph Spectra
  - 7.1 Modularity Matrix
  - 7.2 Laplacian Matrix
  - 7.3 Adjacency Matrix
  - 7.4 Incidence Matrix

- 8 Subgraph Stationarity
- 9 Graph Stationarity Ratio
- 10 Frequency Wavenumber Plots, F-k
- 11 Radon Transform Plots
- 12 Instantaneous Frequency,  $\omega$

## 2 Introduction

### 2.1 Dynamic Network Analysis of Enron Email Network Data

I use the Enron email network data from [John Hopkins](#) which has time, sender and receiver pair format data.

### 2.2 Data Preprocessing

From the JHU data, I have done the following in Excel: - The first column represents seconds elapsed since 1 January 1970, so I convert this in to days - I then add these days to the date to get time stamps for all nodes - From the timestamps, I extract the year field - The network can be partitioned by year in a cumulative manner for DNA

### 2.3 Key Assumption

The key assumption in this analysis is that the nodes can be appended to the original network at time,  $t_0$  with the new nodes from time,  $t+1$ .

## 3 Import Libraries

```
In [1]: import pandas as pd
        import numpy as np
        import networkx as nx
        import seaborn as sns
        import matplotlib.pyplot as plt
        import scipy as sc
%matplotlib inline
sns.set(style="whitegrid", color_codes=True, context='paper')
import random
random.seed(111111111111)
plt.rc('axes', grid=False, titlesize='large', labelsize='medium', labelweight='bold')
plt.rc('lines', linewidth=4)
plt.rc('font', family='serif', size=12, serif='Georgia')
plt.rc('figure', figsize = (15,6), titlesize='large', titleweight='heavy')
plt.rc('grid', linewidth=3)
sns.set_palette('husl')
from scipy.signal import *
```

## 4 Import Data

```
In [2]: data = pd.read_excel("../Data/execs.email.linesnum.xlsx")  
In [3]: data.head()  
  
Out[3]:      sec  to   from          date  year  
0    315522000  24    153 1979-12-31 21:00:00  1979  
1    315522000  24    153 1979-12-31 21:00:00  1979  
2    315522000  29     29 1979-12-31 21:00:00  1979  
3    315522000  29     29 1979-12-31 21:00:00  1979  
4    315522000  29     29 1979-12-31 21:00:00  1979  
  
In [4]: data.min()  
  
Out[4]: sec      315522000  
to        0  
from      0  
date     1979-12-31 21:00:00  
year      1979  
dtype: object  
  
In [5]: data.max()  
  
Out[5]: sec      1024688419  
to        183  
from      183  
date    2002-06-21 19:40:19  
year      2002  
dtype: object
```

## 5 Data Partition

```
In [6]: #year = data['year'].unique()  
year = sorted(set(data['year']))  
year  
  
Out[6]: [1979, 1998, 1999, 2000, 2001, 2002]  
  
In [7]: sorted(set(data['year']))  
  
Out[7]: [1979, 1998, 1999, 2000, 2001, 2002]  
  
In [8]: data.drop(["sec", "date"], axis=1, inplace=True)  
  
In [9]: data.head()  
  
Out[9]:   to   from  year  
0    24    153  1979  
1    24    153  1979  
2    29     29  1979  
3    29     29  1979  
4    29     29  1979
```

## 5.1 Break data into years

```
In [10]: G0 = data[data["year"]==year[0]]  
G1 = data[data["year"]==year[1]]  
G2 = data[data["year"]==year[2]]  
G3 = data[data["year"]==year[3]]  
G4 = data[data["year"]==year[4]]  
G5 = data[data["year"]==year[5]]
```

```
In [11]: G1.size,G1.shape
```

```
Out[11]: (246, (82, 3))
```

```
In [12]: G2.size,G1.shape
```

```
Out[12]: (11145, (82, 3))
```

```
In [13]: G3.size,G1.shape
```

```
Out[13]: (132177, (82, 3))
```

```
In [14]: G3.size,G1.shape
```

```
Out[14]: (132177, (82, 3))
```

```
In [15]: G4.size,G1.shape
```

```
Out[15]: (206664, (82, 3))
```

```
In [16]: G5.size,G1.shape
```

```
Out[16]: (25473, (82, 3))
```

```
In [17]: G1.head()
```

```
Out[17]:      to    from  year  
174    114    169  1998  
175    114    169  1998  
176    114    123  1998  
177    114    123  1998  
178    114    123  1998
```

```
In [18]: G1.tail()
```

```
Out[18]:      to    from  year  
251    112     65  1998  
252    112    114  1998  
253    112    114  1998  
254    112    145  1998  
255    112    145  1998
```

```
In [19]: G2.head()
```

```
Out[19]:      to    from  year
256     114      65  1999
257     114      65  1999
258     114     169  1999
259     114     169  1999
260     114     112  1999
```

```
In [20]: G3.head()
```

```
Out[20]:      to    from  year
3971     82      51  2000
3972     82      51  2000
3973     82      51  2000
3974     82      51  2000
3975     82      51  2000
```

## 5.2 Create networks at different timesteps

### 5.2.1 t = 0

```
In [21]: G0_ = np.asarray(G0.ix[:, :2])
Gt0 = nx.Graph()
Gt0= nx.from_edgelist(G0_)
```

### 5.2.2 t = 1

```
In [22]: G1_ = G1.ix[:, :2]
G1_ = np.concatenate((G1_, G0_), axis=0)
Gt1 = nx.Graph()
Gt1= nx.from_edgelist(G1_)
```

### 5.2.3 t = 2

```
In [23]: G2_ = G2.ix[:, :2]
G2_ = np.concatenate((G2_, G1_), axis=0)
Gt2 = nx.Graph()
Gt2= nx.from_edgelist(G2_)
```

### 5.2.4 t = 3

```
In [24]: G3_ = G3.ix[:, :2]
G3_ = np.concatenate((G3_, G2_), axis=0)
Gt3 = nx.Graph()
Gt3= nx.from_edgelist(G3_)
```

### 5.2.5 t = 4

```
In [25]: G4_ = G4.ix[:, :2]
        G4_ = np.concatenate((G4_, G3_), axis=0)
        Gt4 = nx.Graph()
        Gt4= nx.from_edgelist(G4_)
```

### 5.2.6 t = 5

```
In [26]: G5_ = G5.ix[:, :2]
        G5_ = np.concatenate((G5_, G4_), axis=0)
        Gt5 = nx.Graph()
        Gt5= nx.from_edgelist(G5_)
```

```
In [27]: #Plot graphs together
plt.figure(figsize=(18,18))
plt.suptitle('Enron Email Dynamic Network', fontsize=24)
plt.subplot(321)
nx.draw_spring(Gt0, cmap=plt.cm.inferno, node_color='#FFA500')
plt.title("Graph at time, t = 0", fontsize=18)

plt.subplot(322)
nx.draw_spring(Gt1, cmap=plt.cm.inferno, node_color='#FFA500')
plt.title("Graph at time, t = 1", fontsize=18)

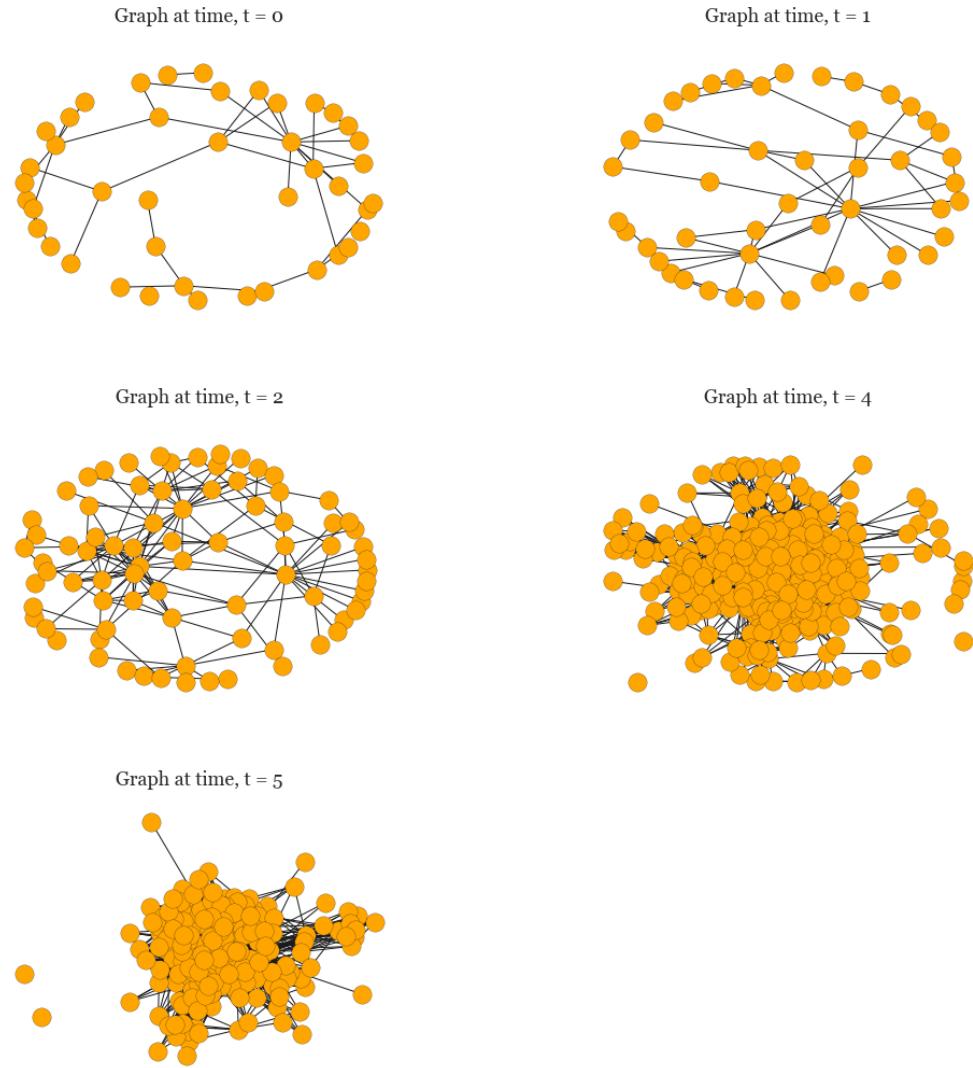
plt.subplot(323)
nx.draw_spring(Gt2, cmap=plt.cm.inferno, node_color='#FFA500')
plt.title("Graph at time, t = 2", fontsize=18)

plt.subplot(324)
nx.draw_spring(Gt3, cmap=plt.cm.inferno, node_color='#FFA500')
plt.title("Graph at time, t = 3", fontsize=18)

plt.subplot(325)
nx.draw_spring(Gt4, cmap=plt.cm.inferno, node_color='#FFA500')
plt.title("Graph at time, t = 4", fontsize=18)

plt.show()
```

## Enron Email Dynamic Network



## 6 Network Statistics

### 6.1 Centrality analysis without averaging

Define some helper functions here

```
In [28]: def get_cent(net):
    degC = nx.degree_centrality(net)
    cloC = nx.closeness_centrality(net)
    betC = nx.betweenness_centrality(net)
```

```

eigC = nx.eigenvector_centrality_numpy(net)
commCC = nx.communicability_centrality(net)
katzC = nx.katz_centrality_numpy(net)
loadC = nx.load_centrality(net)

return [degC,cloC,betC,eigC,commCC,katzC, loadC]

In [29]: def get_val(val):
    return sorted(set(val.values())))

In [30]: def get_top_keys(dictionary, top):
    items = dictionary.items()
    items.sort(reverse=True, key=lambda x: x[1])
    return map(lambda x: x[0], items[:top])

In [31]: def fft_sig(att):
    return sc.fft(get_val(att))

    def hilbert_sig(att):
        return hilbert(get_val(att))

In [32]: def rms(a, axis=None):
    from numpy import mean, sqrt, square
    rms = sqrt(mean(square(a), axis=axis))
    return rms

    def nrms(a,b):
        nrms = rms(a-b) / (rms(a)+ rms(b) )
        return nrms

In [33]: def cossim(x,y):
    from numpy import dot, sqrt
    csim = dot(x,y) / sqrt(dot(x,x))*sqrt(dot(y,y))
    return csim

In [34]: def pairwise_calc(df,func):
    val = []
    for x,y in df.iteritems():
        for z,y in df.iteritems():
            i = 0
            #print(y[i], y[i+1])
            val.append(func(y[i],y[i+1]))
            i=i+1

    return val[:df.shape[0]]

In [35]: def avg_cent(cent):
    avg = sum(set(cent.values()))/len(cent)
    return avg

```

```
In [36]: def cal_stat(net):
    degC = nx.degree_centrality(net)
    cloC = nx.closeness_centrality(net)
    betC = nx.betweenness_centrality(net)
    eigC = nx.eigenvector_centrality_numpy(net)
    algC = nx.algebraic_connectivity(net)
    clustC = nx.average_clustering(net)
    commC = nx.communicability_centrality(net)
    katzC = nx.katz_centrality_numpy(net)
    loadC= nx.load_centrality(net)

    return [avg_cent(degC), avg_cent(cloC), \
            avg_cent(betC), avg_cent(eigC), \
            algC, clustC, avg_cent(commC), \
            avg_cent(katzC), avg_cent(loadC)]
```

### 6.1.1 Calculate all centralities in one go

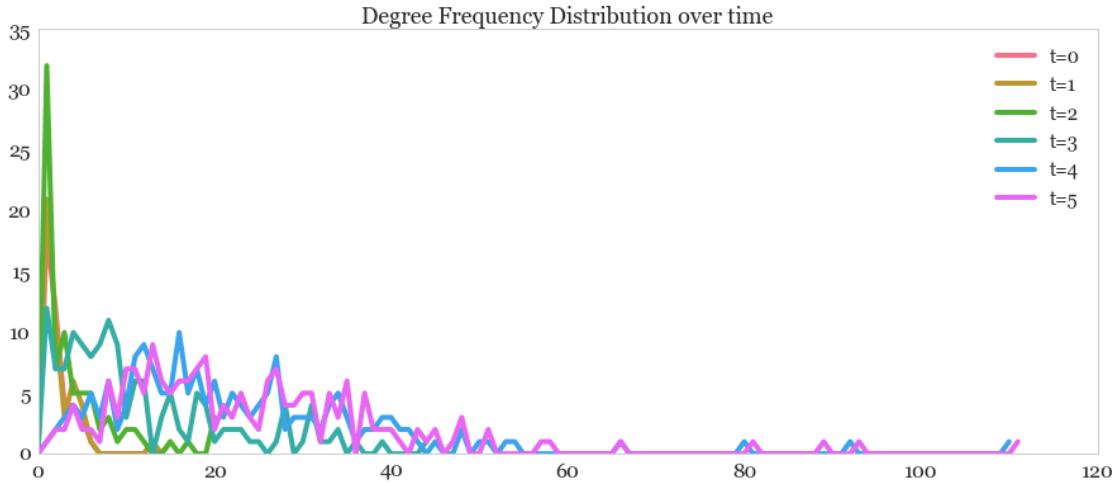
```
In [37]: degC0, cloC0, betC0, eigC0, commuC0, katzC0, loadC0 = get_cent(Gt0)
degC1, cloC1, betC1, eigC1, commuC1, katzC1, loadC1 = get_cent(Gt1)
degC2, cloC2, betC2, eigC2, commuC2, katzC2, loadC2 = get_cent(Gt2)
degC3, cloC3, betC3, eigC3, commuC3, katzC3, loadC3 = get_cent(Gt3)
degC4, cloC4, betC4, eigC4, commuC4, katzC4, loadC4 = get_cent(Gt4)
degC5, cloC5, betC5, eigC5, commuC5, katzC5, loadC5 = get_cent(Gt5)
```

### 6.1.2 Degree Centrality

```
In [38]: plt.title("Degree Frequency Distribution over time", fontsize=18)
plt.plot(nx.degree_histogram(Gt0), label='t=0')
plt.plot(nx.degree_histogram(Gt1), label='t=1')
plt.plot(nx.degree_histogram(Gt2), label='t=2')
plt.plot(nx.degree_histogram(Gt3), label='t=3')
plt.plot(nx.degree_histogram(Gt4), label='t=4')
plt.plot(nx.degree_histogram(Gt5), label='t=5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

Out [38] : <matplotlib.legend.Legend at 0x1ad9e8044e0>

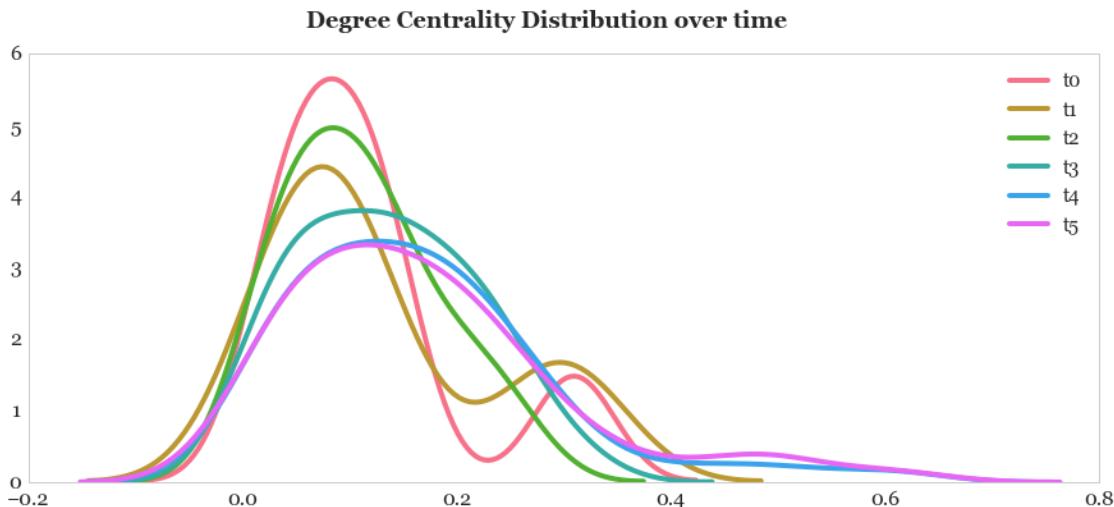


```
In [39]: plt.suptitle('Degree Centrality Distribution over time', fontsize=18)
sns.distplot(get_val(degC0), hist=False, label='t0')
sns.distplot(get_val(degC1), hist=False, label='t1')
sns.distplot(get_val(degC2), hist=False, label='t2')
sns.distplot(get_val(degC3), hist=False, label='t3')
sns.distplot(get_val(degC4), hist=False, label='t4')
sns.distplot(get_val(degC5), hist=False, label='t5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

```
C:\Users\arsha_000\Anaconda3\lib\site-packages\statsmodels\nonparametric\kdetools.py:105:
y = X[:m/2+1] + np.r_[0,X[m/2+1:],0]*1j
```

Out[39]: <matplotlib.legend.Legend at 0x1ad9f4dbc88>

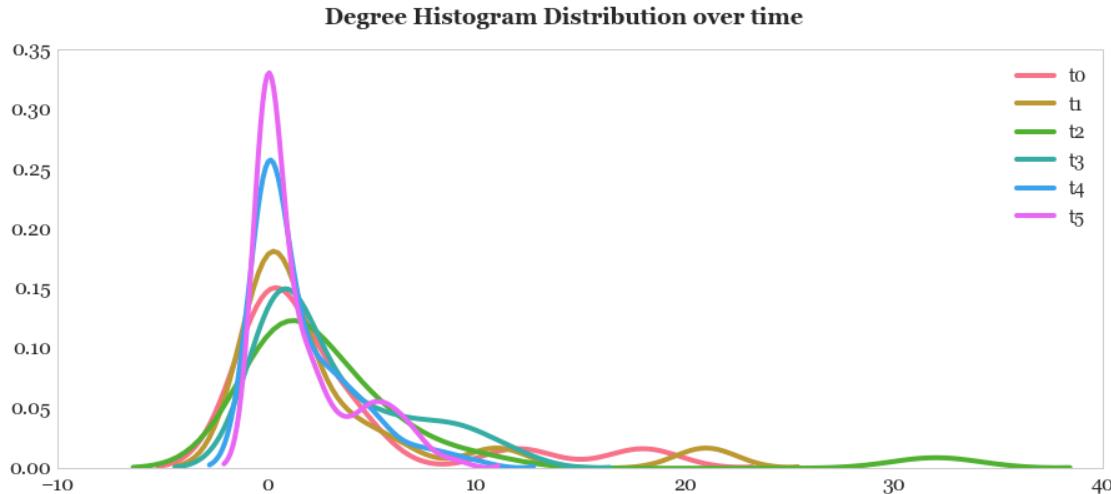


```
In [40]: plt.suptitle('Degree Histogram Distribution over time', fontsize=18)
sns.distplot(nx.degree_histogram(Gt0), hist=False, label='t0')
sns.distplot(nx.degree_histogram(Gt1), hist=False, label='t1')
sns.distplot(nx.degree_histogram(Gt2), hist=False, label='t2')
sns.distplot(nx.degree_histogram(Gt3), hist=False, label='t3')
sns.distplot(nx.degree_histogram(Gt4), hist=False, label='t4')
sns.distplot(nx.degree_histogram(Gt5), hist=False, label='t5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)

C:\Users\arsha_000\Anaconda3\lib\site-packages\statsmodels\nonparametric\kdeutils.py
y = X[:m/2+1] + np.r_[0,X[m/2+1:],0]*1j
```

Out[40]: <matplotlib.legend.Legend at 0x1ad9f55d320>



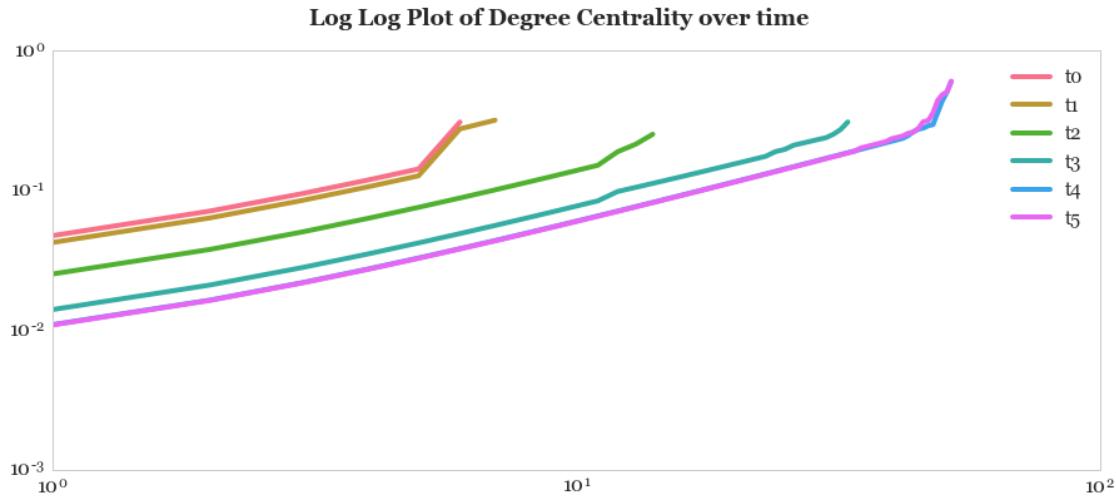
```
In [41]: plt.suptitle('Log Log Plot of Degree Centrality over time', fontsize=18)

plt.loglog(get_val(degC0), label='t0')
plt.loglog(get_val(degC1), label='t1')
plt.loglog(get_val(degC2), label='t2')
plt.loglog(get_val(degC3), label='t3')
plt.loglog(get_val(degC4), label='t4')
plt.loglog(get_val(degC5), label='t5')

plt.yticks(fontsize=16)
```

```
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

Out [41]: <matplotlib.legend.Legend at 0x1ad9f7da940>



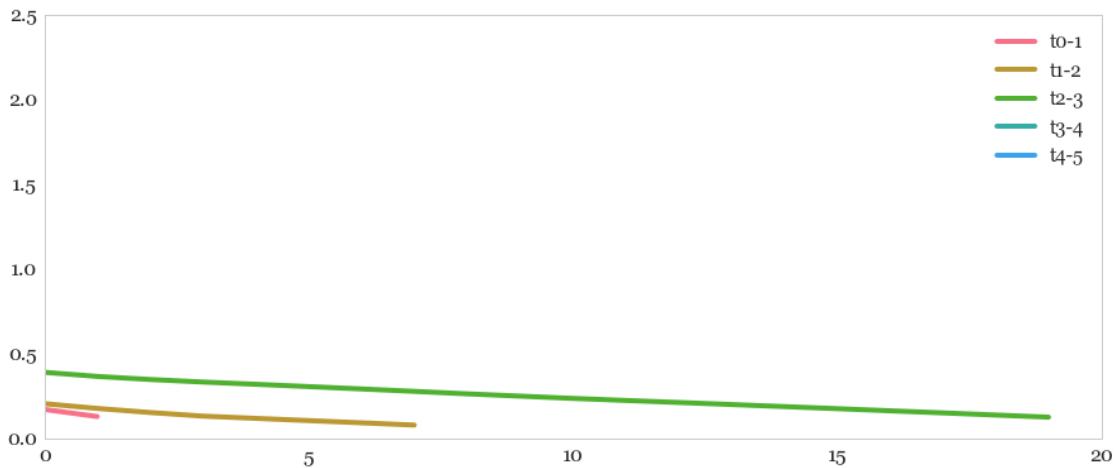
In [42]: plt.suptitle('Adjacent Trace Degree Centrality correlation plot', fontsize=16)

```
plt.plot(np.correlate(get_val(degC0), get_val(degC1)), label='t0-1')
plt.plot(np.correlate(get_val(degC1), get_val(degC2)), label='t1-2')
plt.plot(np.correlate(get_val(degC2), get_val(degC3)), label='t2-3')
plt.plot(np.correlate(get_val(degC3), get_val(degC3)), label='t3-4')
plt.plot(np.correlate(get_val(degC4), get_val(degC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

Out [42]: <matplotlib.legend.Legend at 0x1ad9f77c8d0>

**Adjacent Trace Degree Centrality correlation plot**



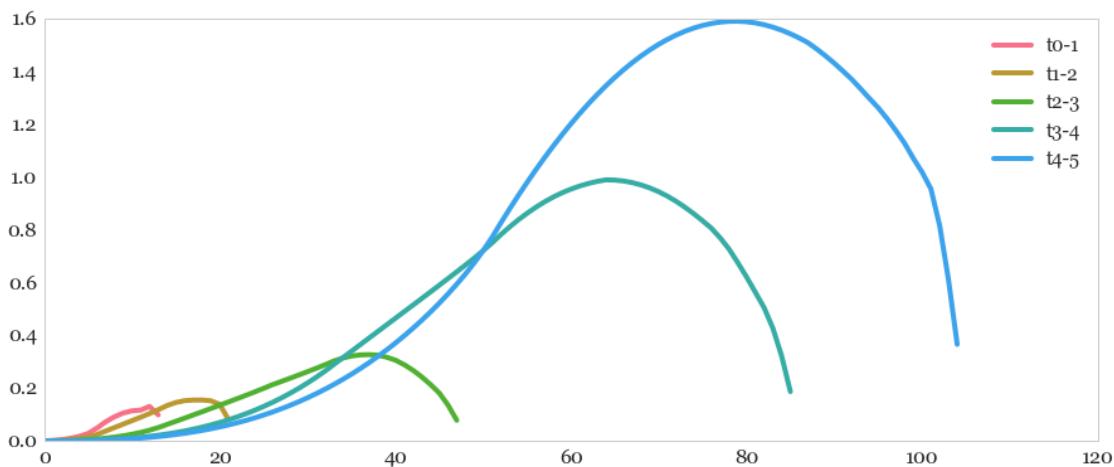
In [43]: plt.suptitle('Adjacent trace Degree Centrality Fourier Domain convolution')

```
plt.plot(fftconvolve(get_val(degC0), get_val(degC1)), label='t0-1')
plt.plot(fftconvolve(get_val(degC1), get_val(degC2)), label='t1-2')
plt.plot(fftconvolve(get_val(degC2), get_val(degC3)), label='t2-3')
plt.plot(fftconvolve(get_val(degC3), get_val(degC4)), label='t3-4')
plt.plot(fftconvolve(get_val(degC4), get_val(degC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

Out [43]: <matplotlib.legend.Legend at 0x1ad9de74cc0>

**Adjacent trace Degree Centrality Fourier Domain convolution plot**



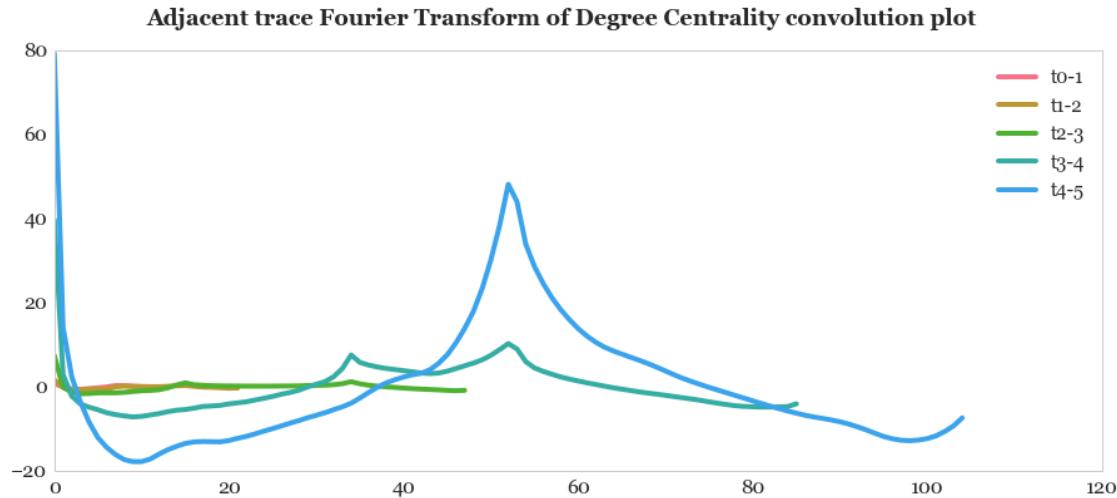
```
In [44]: plt.suptitle('Adjacent trace Fourier Transform of Degree Centrality convolution')

plt.plot(np.convolve(fft_sig(degC0), fft_sig(degC1)), label='t0-1')
plt.plot(np.convolve(fft_sig(degC1), fft_sig(degC2)), label='t1-2')
plt.plot(np.convolve(fft_sig(degC2), fft_sig(degC3)), label='t2-3')
plt.plot(np.convolve(fft_sig(degC3), fft_sig(degC4)), label='t3-4')
plt.plot(np.convolve(fft_sig(degC4), fft_sig(degC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)

C:\Users\arsha_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:482: ComplexWarning:
return array(a, dtype, copy=False, order=order)
```

Out [44]: <matplotlib.legend.Legend at 0x1ad9f1f19b0>



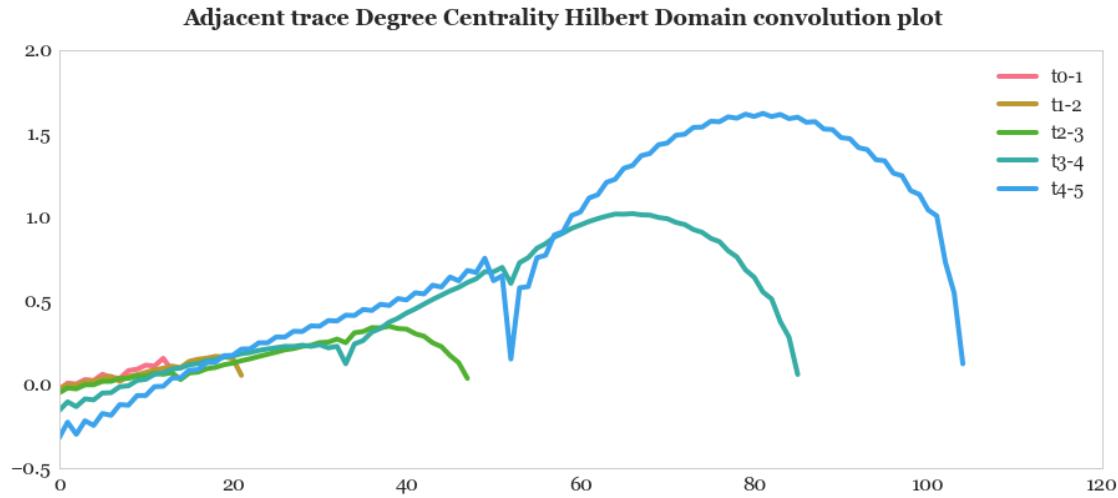
```
In [45]: plt.suptitle('Adjacent trace Degree Centrality Hilbert Domain convolution')

plt.plot(np.convolve(hilbert(get_val(degC0)), hilbert(get_val(degC1))), label='t0-1')
plt.plot(np.convolve(hilbert(get_val(degC1)), hilbert(get_val(degC2))), label='t1-2')
plt.plot(np.convolve(hilbert(get_val(degC2)), hilbert(get_val(degC3))), label='t2-3')
plt.plot(np.convolve(hilbert(get_val(degC3)), hilbert(get_val(degC4))), label='t3-4')
plt.plot(np.convolve(hilbert(get_val(degC4)), hilbert(get_val(degC5))), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

```
C:\Users\arsha_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:482: ComplexWarning
  return array(a, dtype, copy=False, order=order)
```

```
Out[45]: <matplotlib.legend.Legend at 0x1ad9f191438>
```



### 6.1.3 Eigenvector Centrality Histograms

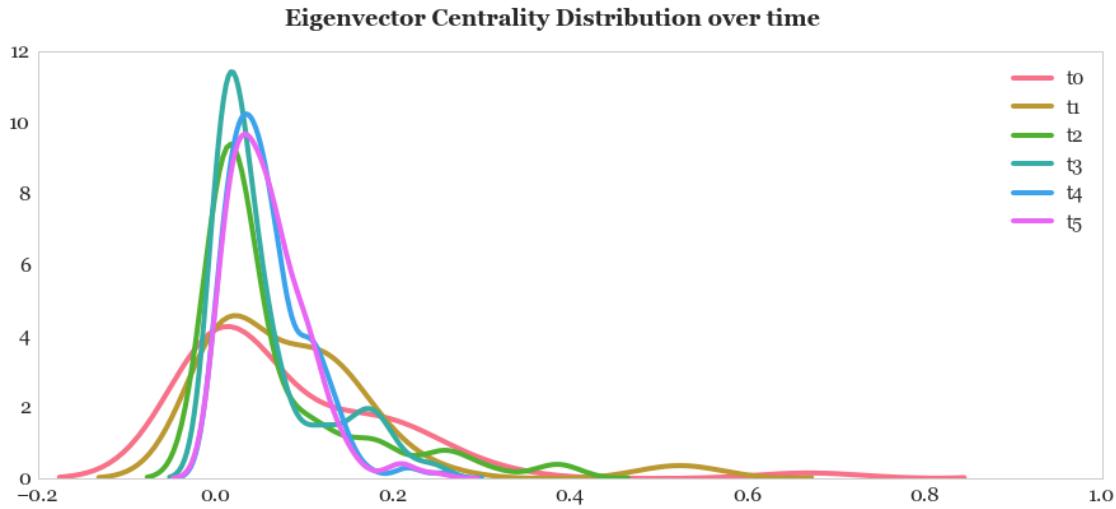
Plotting the Eigenvector Centrality for the different timesteps here. For the first plot it is difficult to discern the trends when all the 6 distributions are plotted together. So in the next series of plots I look at a few a time and its easier to see the change over time. The signal essentially becomes more spiked and squashed over time.

```
In [46]: plt.suptitle('Eigenvector Centrality Distribution over time', fontsize=18)
sns.distplot(get_val(eigC0), hist=False, label='t0')
sns.distplot(get_val(eigC1), hist=False, label='t1')
sns.distplot(get_val(eigC2), hist=False, label='t2')
sns.distplot(get_val(eigC3), hist=False, label='t3')
sns.distplot(get_val(eigC4), hist=False, label='t4')
sns.distplot(get_val(eigC5), hist=False, label='t5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

```
C:\Users\arsha_000\Anaconda3\lib\site-packages\statsmodels\nonparametric\kdetools.py:105:
y = X[:m/2+1] + np.r_[0,X[m/2+1:],0]*1j
```

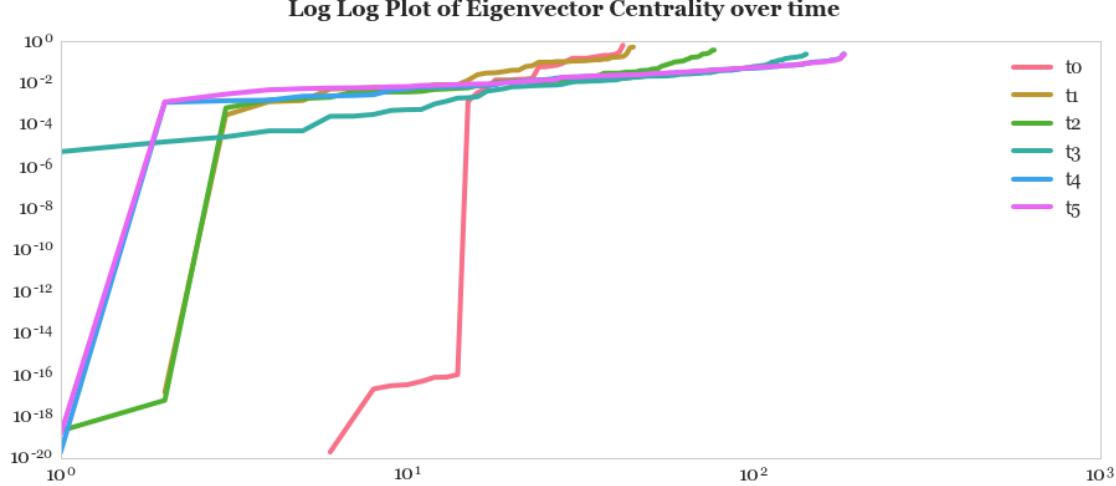
```
Out[46]: <matplotlib.legend.Legend at 0x1ad9ef9a978>
```



```
In [47]: plt.suptitle('Log Log Plot of Eigenvector Centrality over time', fontsize=16)
plt.loglog(get_val(eigC0), label='t0')
plt.loglog(get_val(eigC1), label='t1')
plt.loglog(get_val(eigC2), label='t2')
plt.loglog(get_val(eigC3), label='t3')
plt.loglog(get_val(eigC4), label='t4')
plt.loglog(get_val(eigC5), label='t5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

Out [47]: <matplotlib.legend.Legend at 0x1ad9f2b4c18>

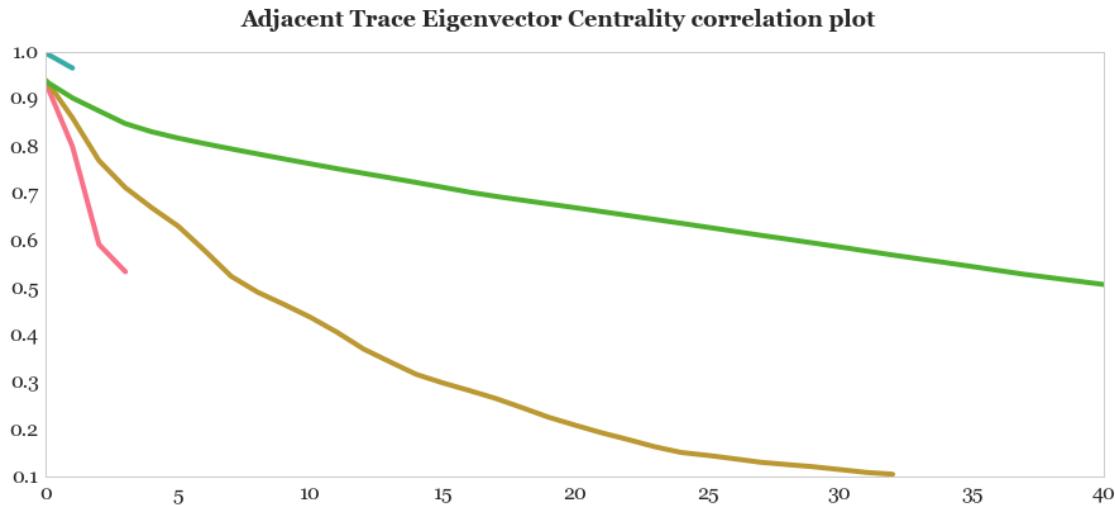


```
In [48]: eigC0_a = np.asarray(get_val(eigC0))
eigC1_a = np.asarray(get_val(eigC1))

In [49]: plt.suptitle('Adjacent Trace Eigenvector Centrality correlation plot', fontweight='bold')
plt.plot(np.correlate(eigC0_a,eigC1_a))
plt.plot(np.correlate(get_val(eigC1),get_val(eigC2)))
plt.plot(np.correlate(get_val(eigC3),get_val(eigC4)))
plt.plot(np.correlate(get_val(eigC4),get_val(eigC5)))

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)

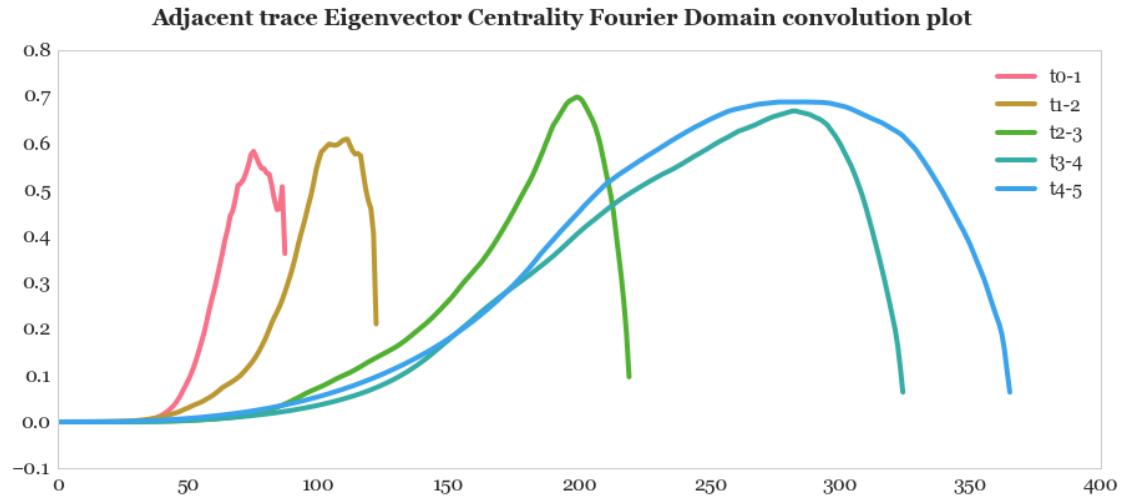
C:\Users\arsha_000\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:519: UserWarning:
warnings.warn("No labelled objects found. "
```



```
In [50]: plt.suptitle('Adjacent trace Eigenvector Centrality Fourier Domain convolution plot', fontweight='bold')
plt.plot(fftconvolve(get_val(eigC0),get_val(eigC1)), label='t0-1')
plt.plot(fftconvolve(get_val(eigC1),get_val(eigC2)), label='t1-2')
plt.plot(fftconvolve(get_val(eigC2),get_val(eigC3)), label='t2-3')
plt.plot(fftconvolve(get_val(eigC3),get_val(eigC4)), label='t3-4')
plt.plot(fftconvolve(get_val(eigC4),get_val(eigC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

```
Out[50]: <matplotlib.legend.Legend at 0x1ada132cb38>
```



```
In [51]: plt.suptitle('Adjacent trace Fourier Transform of Eigenvector Centrality')
```

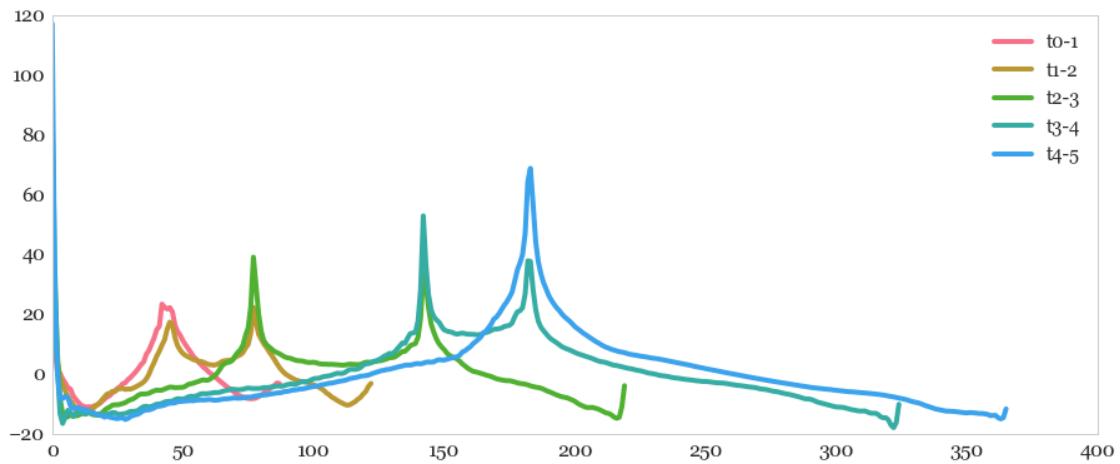
```
plt.plot(np.convolve(fft_sig(eigC0), fft_sig(eigC1)), label='t0-1')
plt.plot(np.convolve(fft_sig(eigC1), fft_sig(eigC2)), label='t1-2')
plt.plot(np.convolve(fft_sig(eigC2), fft_sig(eigC3)), label='t2-3')
plt.plot(np.convolve(fft_sig(eigC3), fft_sig(eigC4)), label='t3-4')
plt.plot(np.convolve(fft_sig(eigC4), fft_sig(eigC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

```
C:\Users\arsha_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:482: ComplexWarning:
return array(a, dtype, copy=False, order=order)
```

```
Out[51]: <matplotlib.legend.Legend at 0x1ada15b7a58>
```

**Adjacent trace Fourier Transform of Eigenvector Centrality convolution plot**



In [52]: plt.suptitle('Adjacent trace Eigenvector Centrality Hilbert Domain convolution')

```
plt.plot(np.convolve(hilbert(get_val(eigC0)), hilbert(get_val(eigC1))), 1
plt.plot(np.convolve(hilbert(get_val(eigC1)), hilbert(get_val(eigC2))), 1
plt.plot(np.convolve(hilbert(get_val(eigC2)), hilbert(get_val(eigC3))), 1
plt.plot(np.convolve(hilbert(get_val(eigC3)), hilbert(get_val(eigC4))), 1
plt.plot(np.convolve(hilbert(get_val(eigC4)), hilbert(get_val(eigC5))), 1

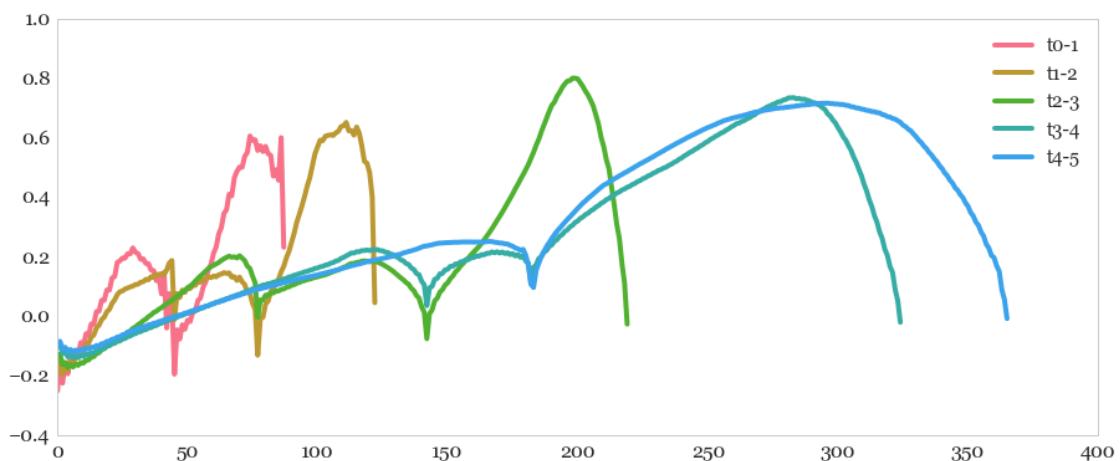
plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

C:\Users\arsha\_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:482: ComplexWarning: Casting float32 to float64 in inner loop of ufunc 'inner' from type 'float32' to 'float64' overwriting a scalar

return array(a, dtype, copy=False, order=order)

Out[52]: <matplotlib.legend.Legend at 0x1ada1832cc0>

**Adjcent trace Eigenvector Centrality Hilbert Domain convolution plot**



```
In [53]: print(np.correlate(eigC0_a,eigC1_a))
      print(np.correlate(eigC0_a,eigC1_a)/np.sqrt(np.correlate(eigC0_a,eigC1_a)))

[ 0.934373   0.8003439   0.59281644  0.53482695]
[ 0.96662971  0.89461941  0.76994574  0.73131864]
```

#### 6.1.4 Closeness Centrality Histograms

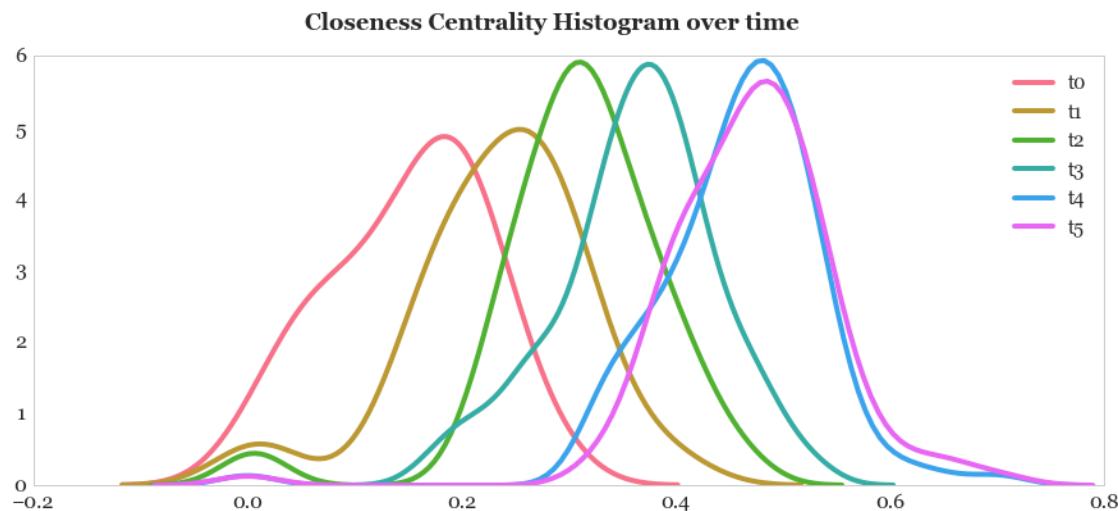
**The Closeness Centrality shows a much better evolution over time than the Eigenvector Centrality Histograms**

```
In [54]: plt.suptitle('Closeness Centrality Histogram over time', fontsize=18)
      sns.distplot(get_val(cloC0), hist=False, label='t0')
      sns.distplot(get_val(cloC1), hist=False, label='t1')
      sns.distplot(get_val(cloC2), hist=False, label='t2')
      sns.distplot(get_val(cloC3), hist=False, label='t3')
      sns.distplot(get_val(cloC4), hist=False, label='t4')
      sns.distplot(get_val(cloC5), hist=False, label='t5')

      plt.yticks(fontsize=16)
      plt.xticks(fontsize=16)
      plt.legend(loc=1, fontsize=15)

C:\Users\arsha_000\Anaconda3\lib\site-packages\statsmodels\nonparametric\kdetools.py
y = X[:m/2+1] + np.r_[0,X[m/2+1:],0]*1j
```

Out [54]: <matplotlib.legend.Legend at 0x1ad9fb6cf60>

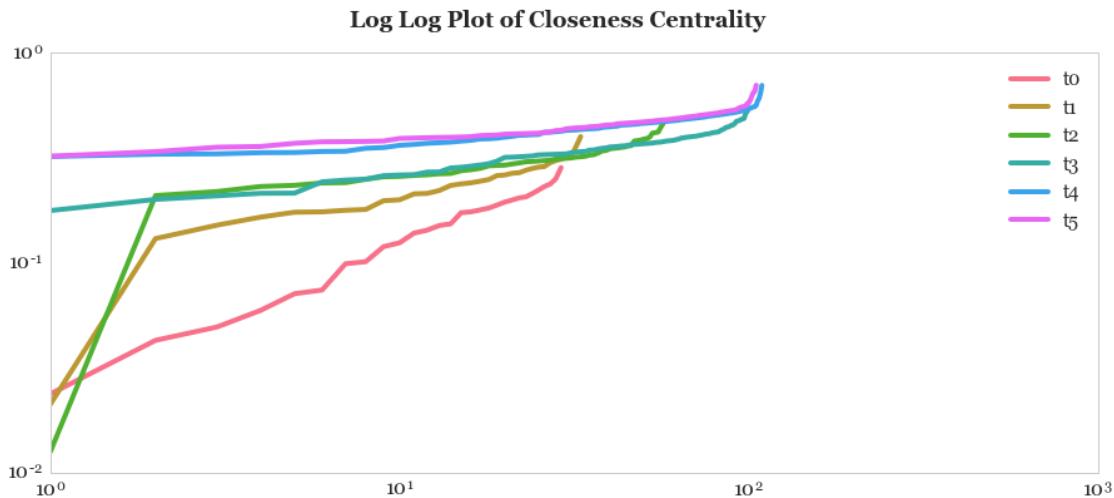


```
In [55]: plt.suptitle('Log Log Plot of Closeness Centrality', fontsize=18)

plt.loglog(get_val(cloC0),label='t0')
plt.loglog(get_val(cloC1),label='t1')
plt.loglog(get_val(cloC2),label='t2')
plt.loglog(get_val(cloC3),label='t3')
plt.loglog(get_val(cloC4),label='t4')
plt.loglog(get_val(cloC5),label='t5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

Out [55]: <matplotlib.legend.Legend at 0x1ada186fa90>



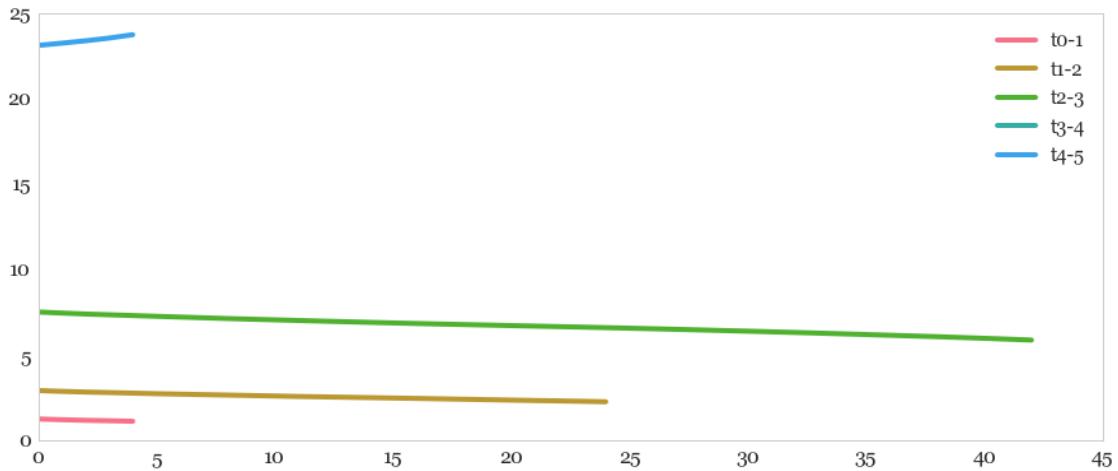
```
In [56]: plt.suptitle('Adjacent Trace Closeness Centrality correlation plot', fontsize=18)

plt.plot(np.correlate(get_val(cloC0),get_val(cloC1)),label='t0-1')
plt.plot(np.correlate(get_val(cloC1),get_val(cloC2)),label='t1-2')
plt.plot(np.correlate(get_val(cloC2),get_val(cloC3)),label='t2-3')
plt.plot(np.correlate(get_val(cloC3),get_val(cloC3)),label='t3-4')
plt.plot(np.correlate(get_val(cloC4),get_val(cloC5)),label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

Out [56]: <matplotlib.legend.Legend at 0x1ad9facf390>

**Adjacent Trace Closeness Centrality correlation plot**



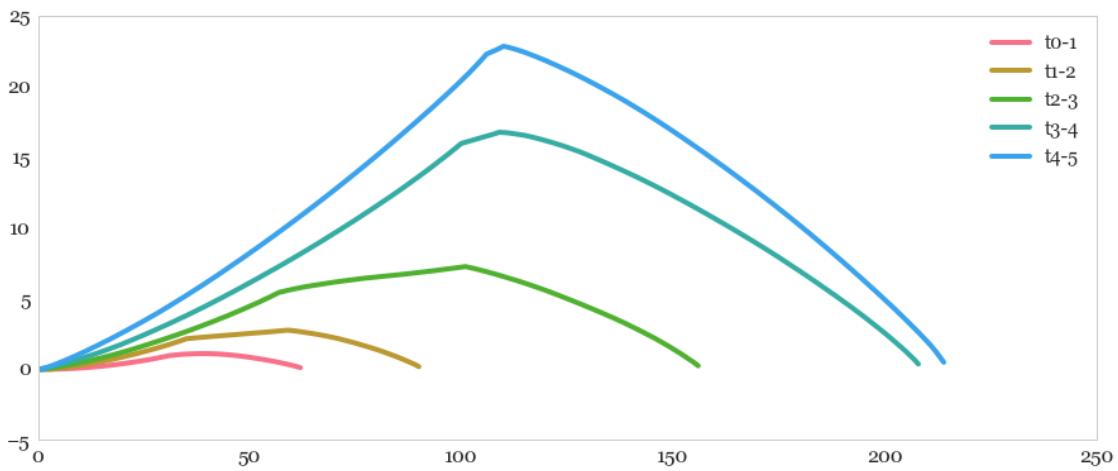
In [57]: plt.suptitle('Adjacent trace Closeness Centrality Fourier Domain convolution')

```
plt.plot(fftconvolve(get_val(cloC0),get_val(cloC1)),label='t0-1')
plt.plot(fftconvolve(get_val(cloC1),get_val(cloC2)), label='t1-2')
plt.plot(fftconvolve(get_val(cloC2),get_val(cloC3)), label='t2-3')
plt.plot(fftconvolve(get_val(cloC3),get_val(cloC4)), label='t3-4')
plt.plot(fftconvolve(get_val(cloC4),get_val(cloC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

Out [57]: <matplotlib.legend.Legend at 0x1ada18e9c50>

**Adjacent trace Closeness Centrality Fourier Domain convolution plot**



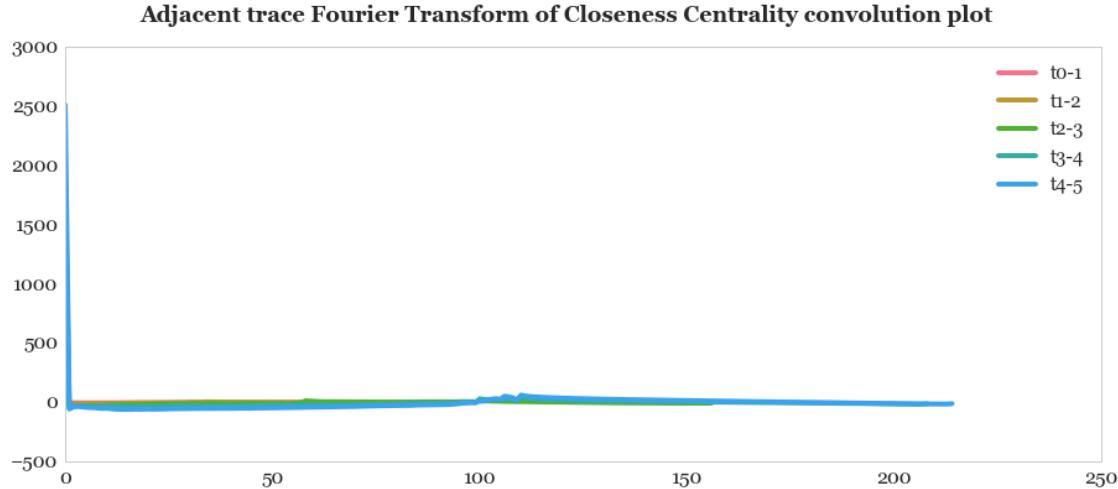
```
In [58]: plt.suptitle('Adjacent trace Fourier Transform of Closeness Centrality convolution plot')

plt.plot(np.convolve(fft_sig(cloC0), fft_sig(cloC1)), label='t0-1')
plt.plot(np.convolve(fft_sig(cloC1), fft_sig(cloC2)), label='t1-2')
plt.plot(np.convolve(fft_sig(cloC2), fft_sig(cloC3)), label='t2-3')
plt.plot(np.convolve(fft_sig(cloC3), fft_sig(cloC4)), label='t3-4')
plt.plot(np.convolve(fft_sig(cloC4), fft_sig(cloC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)

C:\Users\arsha_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:482: ComplexWarning:
return array(a, dtype, copy=False, order=order)
```

Out [58]: <matplotlib.legend.Legend at 0x1ada1927358>



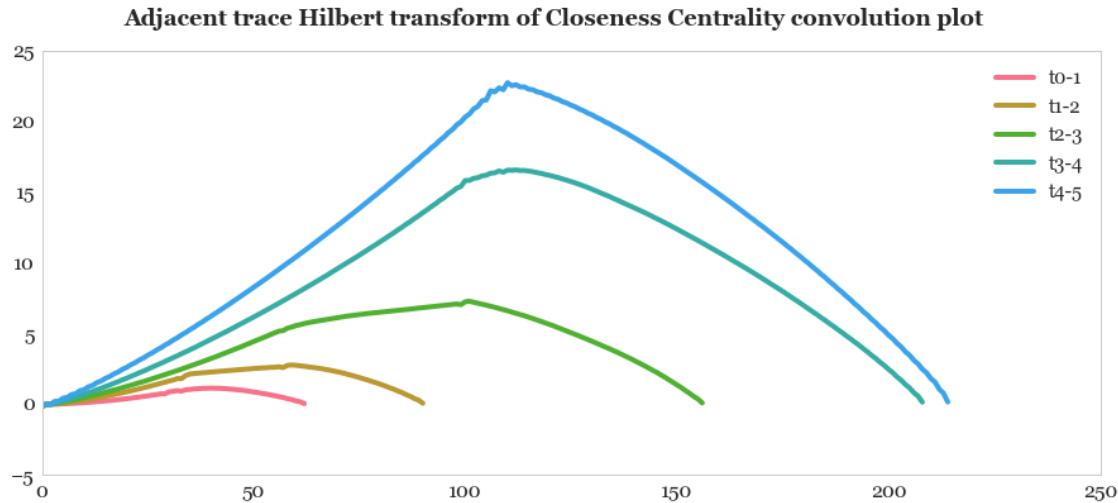
```
In [59]: plt.suptitle('Adjacent trace Hilbert transform of Closeness Centrality convolution plot')

plt.plot(np.convolve(hilbert_sig(cloC0), hilbert_sig(cloC1)), label='t0-1')
plt.plot(np.convolve(hilbert_sig(cloC1), hilbert_sig(cloC2)), label='t1-2')
plt.plot(np.convolve(hilbert_sig(cloC2), hilbert_sig(cloC3)), label='t2-3')
plt.plot(np.convolve(hilbert_sig(cloC3), hilbert_sig(cloC4)), label='t3-4')
plt.plot(np.convolve(hilbert_sig(cloC4), hilbert_sig(cloC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)

C:\Users\arsha_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:482: ComplexWarning:
return array(a, dtype, copy=False, order=order)
```

```
Out[59]: <matplotlib.legend.Legend at 0x1ada19fbf98>
```



### 6.1.5 Betweenness Centrality Histogram

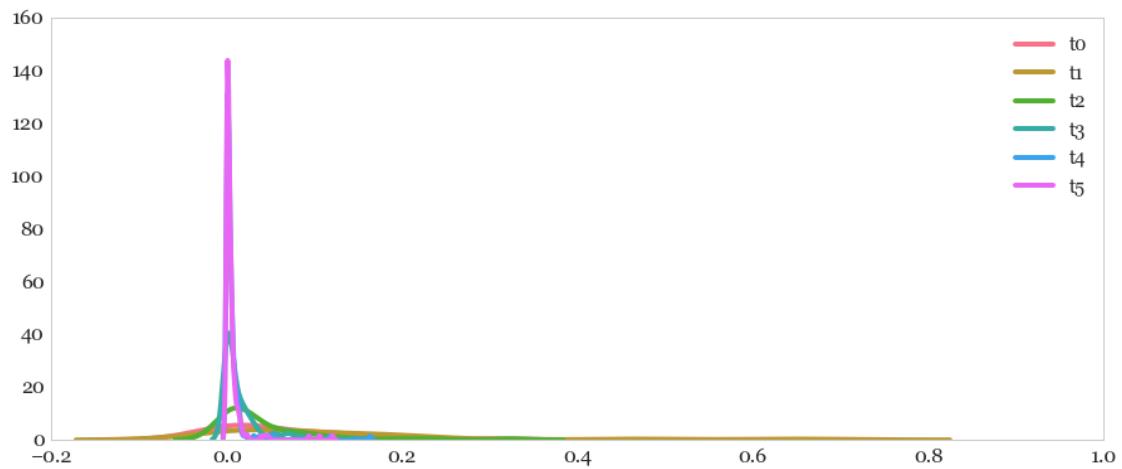
```
In [60]: plt.suptitle('Betweenness Centrality over time', fontsize=18)
sns.distplot(get_val(betC0), hist=False, label='t0')
sns.distplot(get_val(betC1), hist=False, label='t1')
sns.distplot(get_val(betC2), hist=False, label='t2')
sns.distplot(get_val(betC3), hist=False, label='t3')
sns.distplot(get_val(betC4), hist=False, label='t4')
sns.distplot(get_val(betC5), hist=False, label='t5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)

C:\Users\arsha_000\Anaconda3\lib\site-packages\statsmodels\nonparametric\kdetools.py
y = X[:m/2+1] + np.r_[0,X[m/2+1:],0]*1j
```

```
Out[60]: <matplotlib.legend.Legend at 0x1ada1fe51d0>
```

**Betweenness Centrality over time**



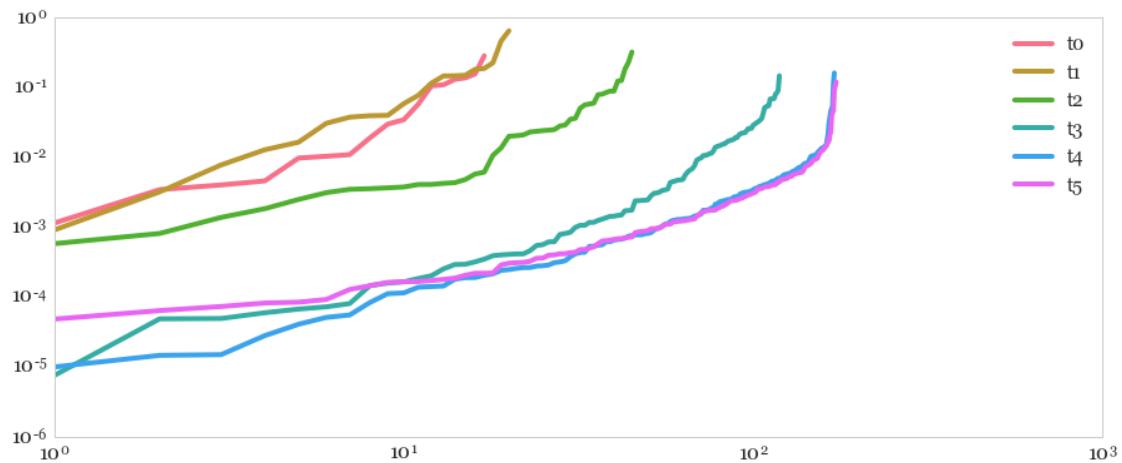
In [61]: `plt.suptitle('Log Log Plot of Betweenness Centrality over time', fontsize=16)`

```
plt.loglog(get_val(betC0), label='t0')
plt.loglog(get_val(betC1), label='t1')
plt.loglog(get_val(betC2), label='t2')
plt.loglog(get_val(betC3), label='t3')
plt.loglog(get_val(betC4), label='t4')
plt.loglog(get_val(betC5), label='t5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

Out[61]: <matplotlib.legend.Legend at 0x1ada254de80>

**Log Log Plot of Betweenness Centrality over time**

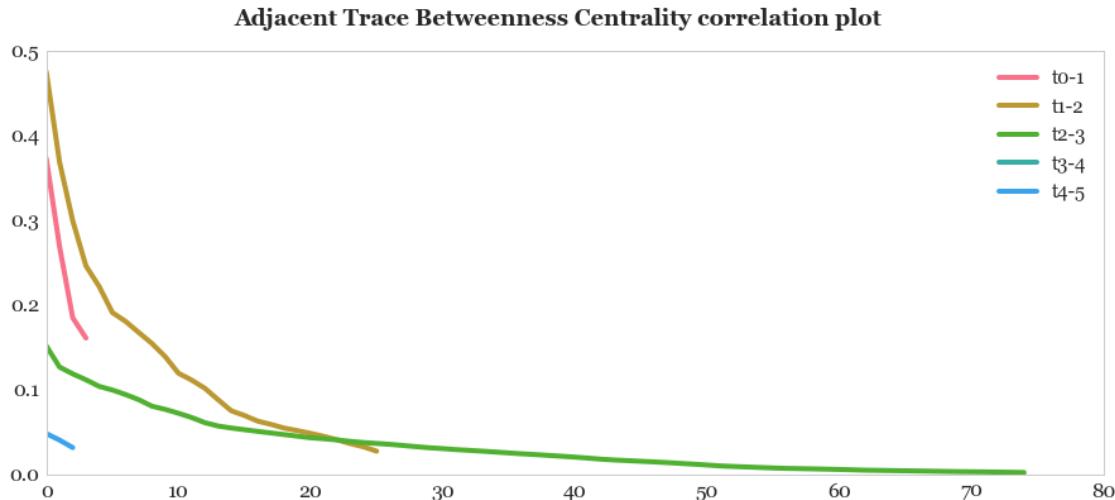


```
In [62]: plt.suptitle('Adjacent Trace Betweenness Centrality correlation plot', fontweight='bold')

plt.plot(np.correlate(get_val(betC0), get_val(betC1)), label='t0-1')
plt.plot(np.correlate(get_val(betC1), get_val(betC2)), label='t1-2')
plt.plot(np.correlate(get_val(betC2), get_val(betC3)), label='t2-3')
plt.plot(np.correlate(get_val(betC3), get_val(betC3)), label='t3-4')
plt.plot(np.correlate(get_val(betC4), get_val(betC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

Out [62]: <matplotlib.legend.Legend at 0x1ada5433e10>



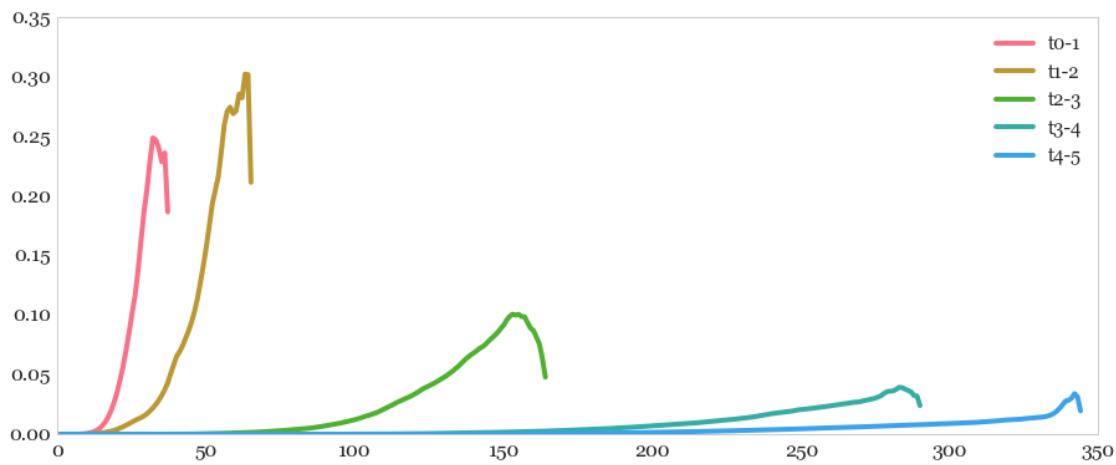
```
In [63]: plt.suptitle('Adjacent trace Betweenness Centrality Fourier Domain convolution correlation plot', fontweight='bold')

plt.plot(fftconvolve(get_val(betC0), get_val(betC1)), label='t0-1')
plt.plot(fftconvolve(get_val(betC1), get_val(betC2)), label='t1-2')
plt.plot(fftconvolve(get_val(betC2), get_val(betC3)), label='t2-3')
plt.plot(fftconvolve(get_val(betC3), get_val(betC4)), label='t3-4')
plt.plot(fftconvolve(get_val(betC4), get_val(betC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

Out [63]: <matplotlib.legend.Legend at 0x1ada55ea080>

**Adjacent trace Betweenness Centrality Fourier Domain convolution plot**



In [64]: `plt.suptitle('Adjacent trace Fourier Transform of Betweenness Centrality convolution plot')`

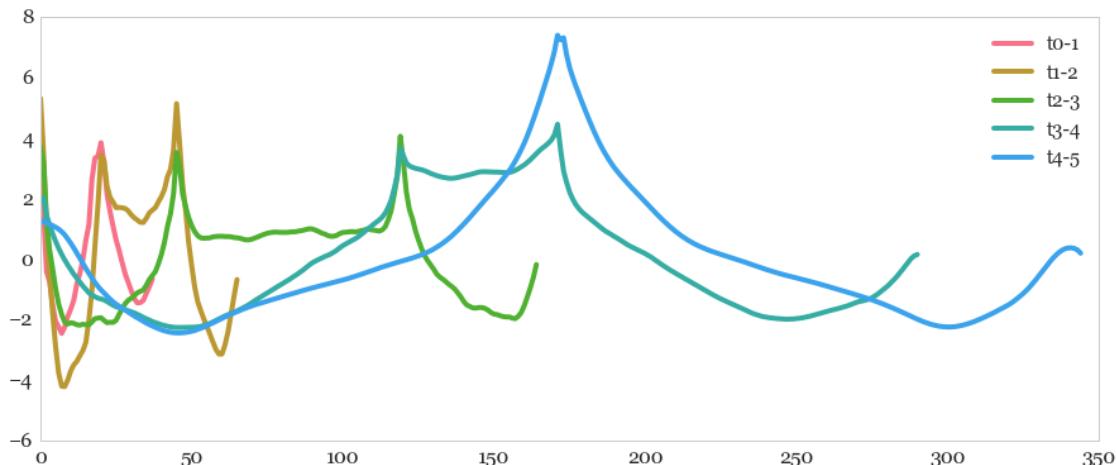
```
plt.plot(np.convolve(fft_sig(betC0),fft_sig(betC1)),label='t0-1')
plt.plot(np.convolve(fft_sig(betC1),fft_sig(betC2)),label='t1-2')
plt.plot(np.convolve(fft_sig(betC2),fft_sig(betC3)),label='t2-3')
plt.plot(np.convolve(fft_sig(betC3),fft_sig(betC4)),label='t3-4')
plt.plot(np.convolve(fft_sig(betC4),fft_sig(betC5)),label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

C:\Users\arsha\_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:482: ComplexWarning: Casting complex values to real discards the imaginary part
return array(a, dtype, copy=False, order=order)

Out[64]: <matplotlib.legend.Legend at 0x1ada5671400>

**Adjacent trace Fourier Transform of Betweenness Centrality convolution plot**



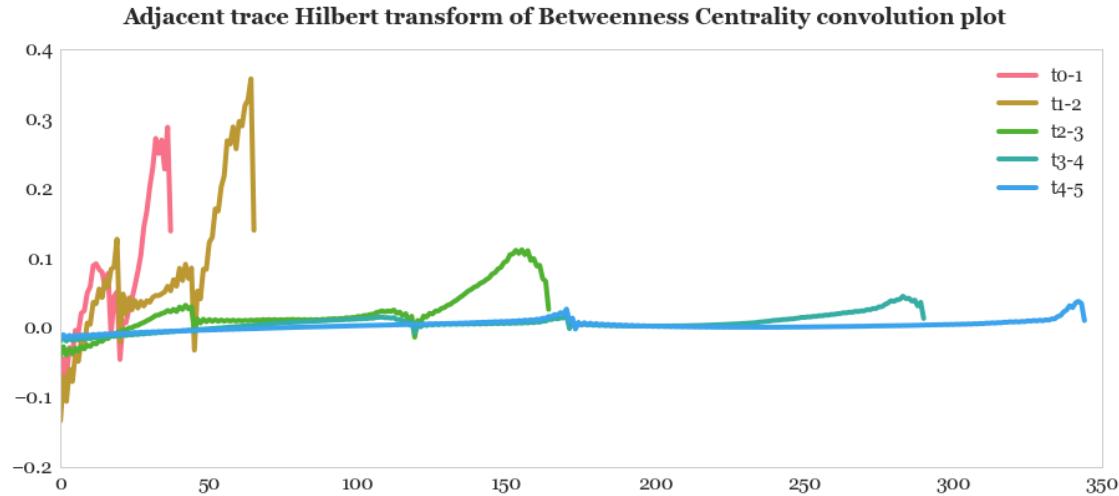
```
In [65]: plt.suptitle('Adjacent trace Hilbert transform of Betweenness Centrality')

plt.plot(np.convolve(hilbert_sig(betC0), hilbert_sig(betC1)), label='t0-1')
plt.plot(np.convolve(hilbert_sig(betC1), hilbert_sig(betC2)), label='t1-2')
plt.plot(np.convolve(hilbert_sig(betC2), hilbert_sig(betC3)), label='t2-3')
plt.plot(np.convolve(hilbert_sig(betC3), hilbert_sig(betC4)), label='t3-4')
plt.plot(np.convolve(hilbert_sig(betC4), hilbert_sig(betC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)

C:\Users\arsha_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:482: ComplexWarning:
return array(a, dtype, copy=False, order=order)
```

Out [65]: <matplotlib.legend.Legend at 0x1ada4fe6ba8>



### 6.1.6 Communicability Centrality Histograms

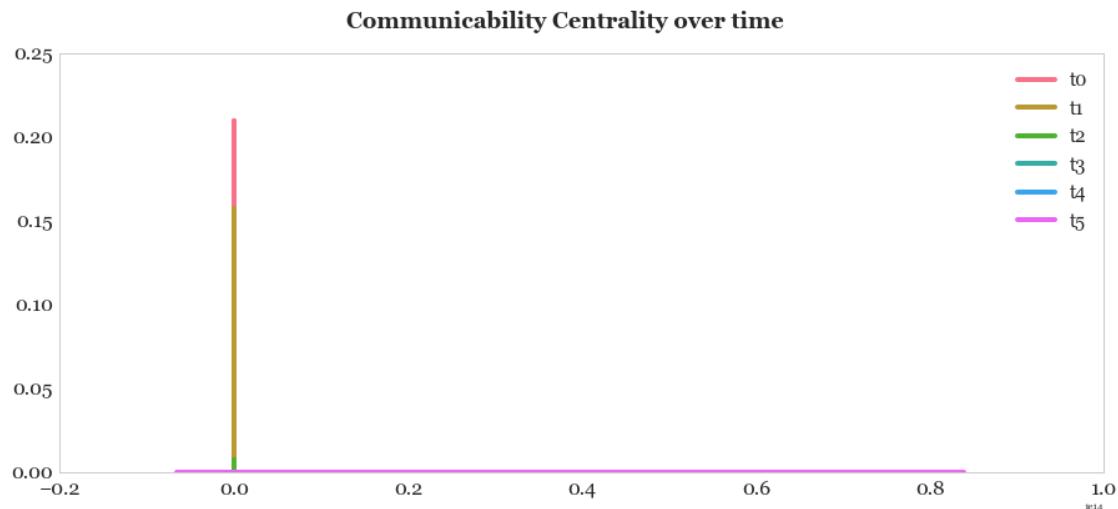
```
In [66]: plt.suptitle('Communicability Centrality over time', fontsize=18)
sns.distplot(get_val(commuC0), hist=False, label='t0')
sns.distplot(get_val(commuC1), hist=False, label='t1')
sns.distplot(get_val(commuC2), hist=False, label='t2')
sns.distplot(get_val(commuC3), hist=False, label='t3')
sns.distplot(get_val(commuC4), hist=False, label='t4')
sns.distplot(get_val(commuC5), hist=False, label='t5')
```

```
plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

```
C:\Users\arsha_000\Anaconda3\lib\site-packages\statsmodels\nonparametric\kdetools.py
```

```
y = X[:m/2+1] + np.r_[0,X[m/2+1:],0]*1j
```

```
Out[66]: <matplotlib.legend.Legend at 0x1ada4f08240>
```

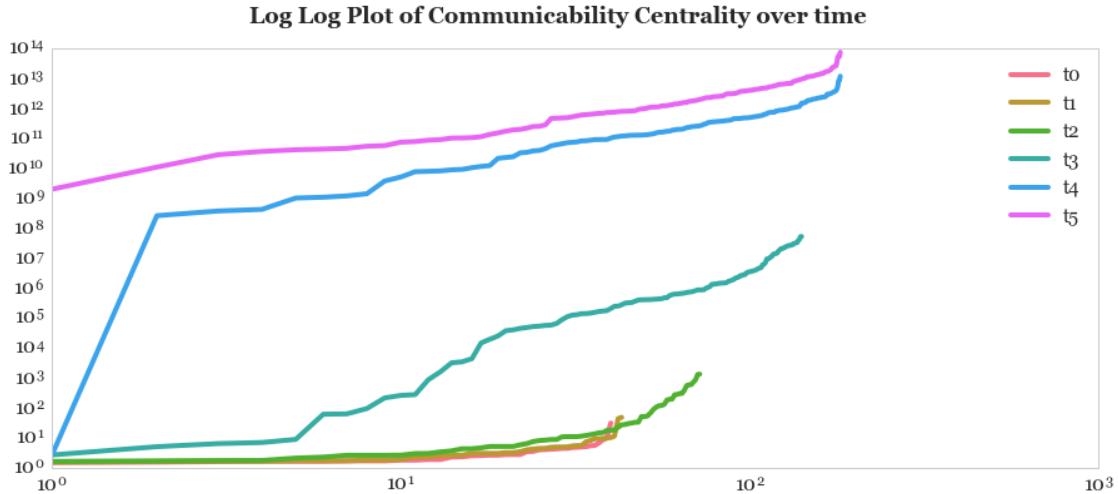


```
In [67]: plt.suptitle('Log Log Plot of Communicability Centrality over time', font
```

```
plt.loglog(get_val(commuC0), label='t0')
plt.loglog(get_val(commuC1), label='t1')
plt.loglog(get_val(commuC2), label='t2')
plt.loglog(get_val(commuC3), label='t3')
plt.loglog(get_val(commuC4), label='t4')
plt.loglog(get_val(commuC5), label='t5')

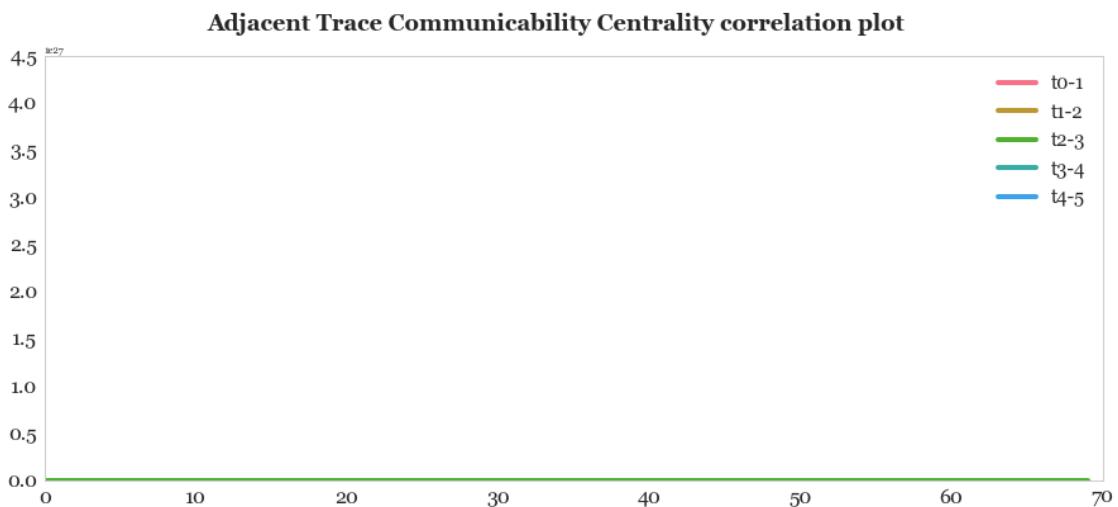
plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

```
Out[67]: <matplotlib.legend.Legend at 0x1ada514ccc0>
```



```
In [68]: plt.suptitle('Adjacent Trace Communicability Centrality correlation plot',  
plt.plot(np.correlate(get_val(commuC0),get_val(commuC1)),label='t0-1')  
plt.plot(np.correlate(get_val(commuC1),get_val(commuC2)),label='t1-2')  
plt.plot(np.correlate(get_val(commuC2),get_val(commuC3)),label='t2-3')  
plt.plot(np.correlate(get_val(commuC3),get_val(commuC3)),label='t3-4')  
plt.plot(np.correlate(get_val(commuC4),get_val(commuC5)),label='t4-5')  
  
plt.yticks(fontsize=16)  
plt.xticks(fontsize=16)  
plt.legend(loc=1, fontsize=15)
```

Out[68]: <matplotlib.legend.Legend at 0x1ada1d7aa90>

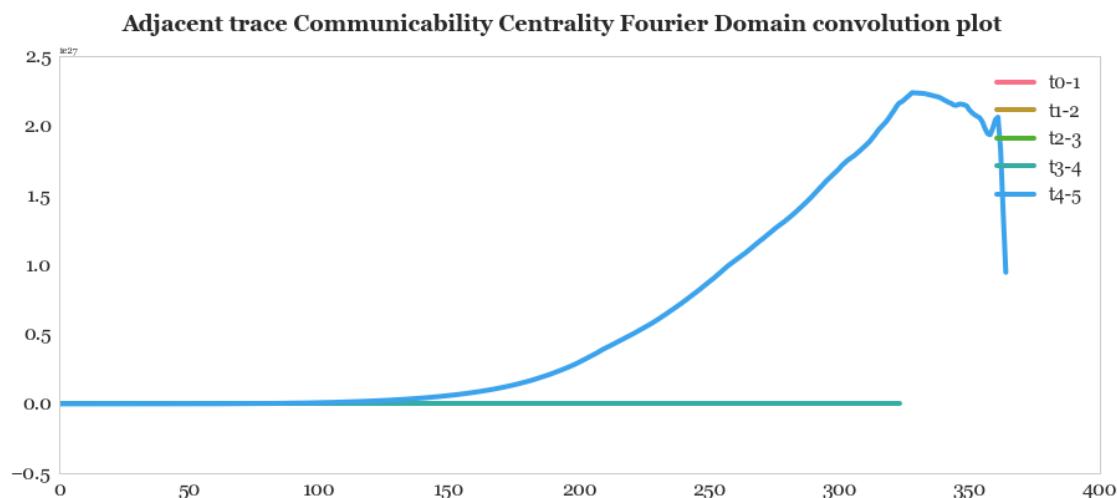


```
In [69]: plt.suptitle('Adjacent trace Communicability Centrality Fourier Domain convolution plot')

plt.plot(fftconvolve(get_val(commuC0),get_val(commuC1)),label='t0-1')
plt.plot(fftconvolve(get_val(commuC1),get_val(commuC2)), label='t1-2')
plt.plot(fftconvolve(get_val(commuC2),get_val(commuC3)), label='t2-3')
plt.plot(fftconvolve(get_val(commuC3),get_val(commuC4)), label='t3-4')
plt.plot(fftconvolve(get_val(commuC4),get_val(commuC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

Out[69]: <matplotlib.legend.Legend at 0x1ada1bdecc0>



In [70]: plt.suptitle('Adjacent trace Fourier Transform of Communicability Centrality')

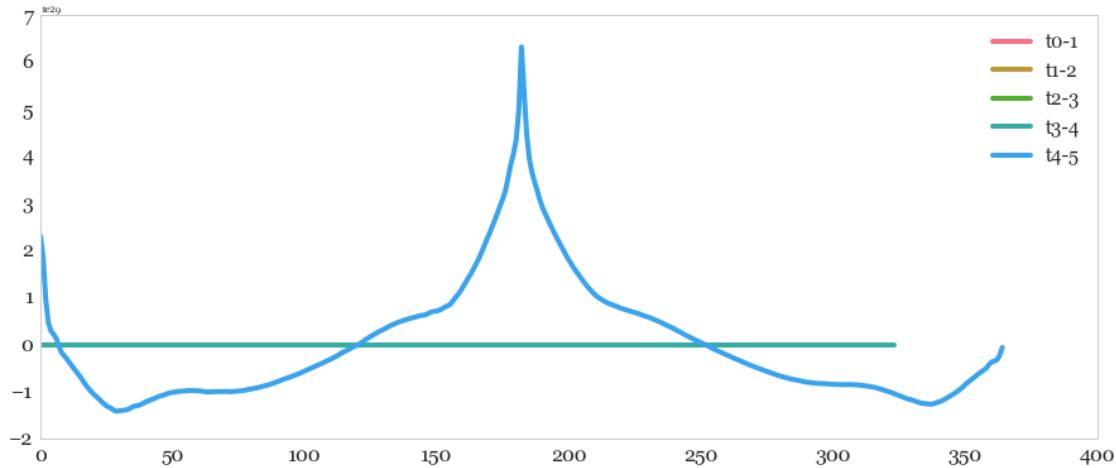
```
plt.plot(np.convolve(fft_sig(commuC0),fft_sig(commuC1)),label='t0-1')
plt.plot(np.convolve(fft_sig(commuC1),fft_sig(commuC2)),label='t1-2')
plt.plot(np.convolve(fft_sig(commuC2),fft_sig(commuC3)),label='t2-3')
plt.plot(np.convolve(fft_sig(commuC3),fft_sig(commuC4)),label='t3-4')
plt.plot(np.convolve(fft_sig(commuC4),fft_sig(commuC5)),label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

C:\Users\arsha\_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:482: ComplexWarning: Casting float32 to ComplexFloat is deprecated. Use np.complex64 instead.
 return array(a, dtype, copy=False, order=order)

Out[70]: <matplotlib.legend.Legend at 0x1ada4e09ac8>

**Adjacent trace Fourier Transform of Communicability Centrality convolution plot**



In [71]: `plt.suptitle('Adjacent trace Hilbert transform of Communicability Centrality convolution plot')`

```
plt.plot(np.convolve(hilbert_sig(commuC0), hilbert_sig(commuC1)), label='t0-1')
plt.plot(np.convolve(hilbert_sig(commuC1), hilbert_sig(commuC2)), label='t1-2')
plt.plot(np.convolve(hilbert_sig(commuC2), hilbert_sig(commuC3)), label='t2-3')
plt.plot(np.convolve(hilbert_sig(commuC3), hilbert_sig(commuC4)), label='t3-4')
plt.plot(np.convolve(hilbert_sig(commuC4), hilbert_sig(commuC5)), label='t4-5')

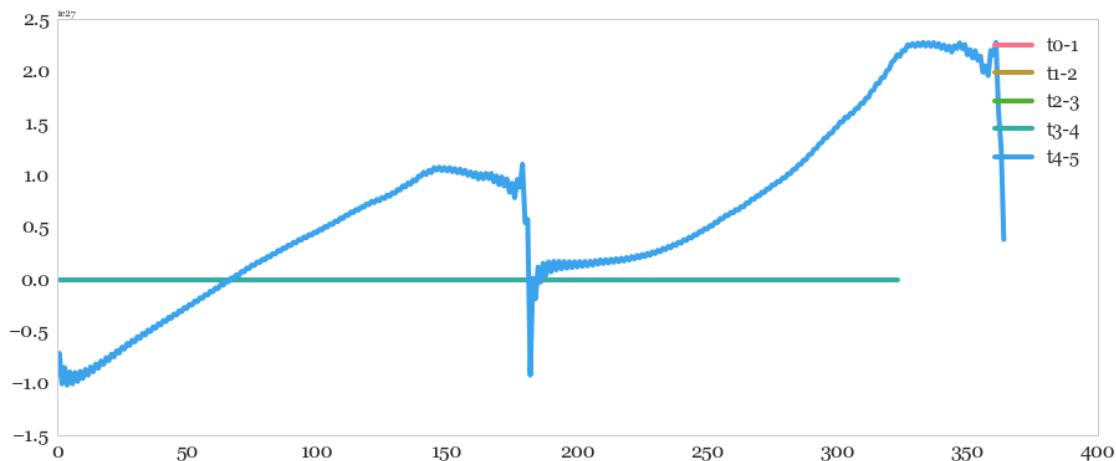
plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

C:\Users\arsha\_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:482: ComplexWarning: Casting float32 to float64 in inner loop of ufunc 'inner' from type 'float32' to type 'float64' in scalar multiplication

return array(a, dtype, copy=False, order=order)

Out[71]: <matplotlib.legend.Legend at 0x1ada4e99ba8>

**Adjacent trace Hilbert transform of Communicability Centrality convolution plot**



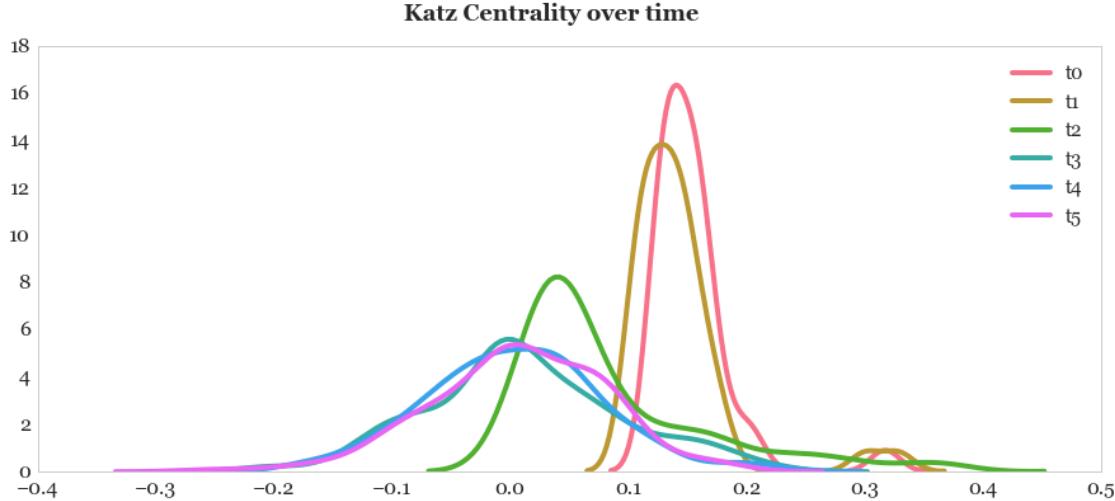
### 6.1.7 Katz Centrality Histograms

```
In [72]: plt.suptitle('Katz Centrality over time', fontsize=18)
sns.distplot(get_val(katzC0), hist=False, label='t0')
sns.distplot(get_val(katzC1), hist=False, label='t1')
sns.distplot(get_val(katzC2), hist=False, label='t2')
sns.distplot(get_val(katzC3), hist=False, label='t3')
sns.distplot(get_val(katzC4), hist=False, label='t4')
sns.distplot(get_val(katzC5), hist=False, label='t5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)

C:\Users\arsha_000\Anaconda3\lib\site-packages\statsmodels\nonparametric\kdeutils.py
y = X[:m/2+1] + np.r_[0,X[m/2+1:],0]*1j
```

```
Out[72]: <matplotlib.legend.Legend at 0x1ada5d077b8>
```



```
In [73]: plt.suptitle('Log Log Plot of Katz Centrality over time', fontsize=18)

plt.loglog(get_val(katzC0), label='t0')
plt.loglog(get_val(katzC1), label='t1')
plt.loglog(get_val(katzC2), label='t2')
plt.loglog(get_val(katzC3), label='t3')
plt.loglog(get_val(katzC4), label='t4')
```

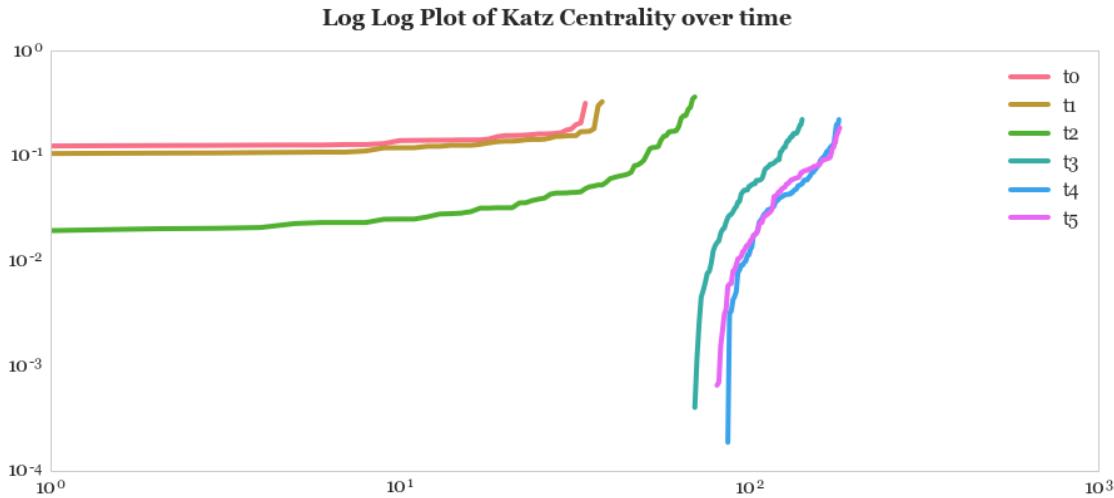
```

plt.loglog(get_val(katzC5), label='t5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)

```

Out[73]: <matplotlib.legend.Legend at 0x1ada76f8e10>



In [74]: plt.suptitle('Adjacent Trace Katz Centrality correlation plot', fontsize=1)

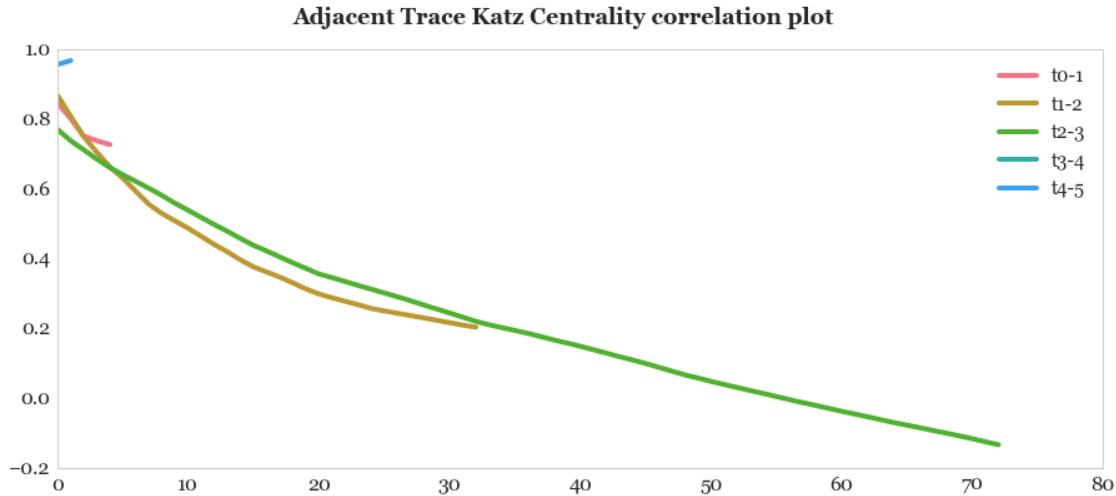
```

plt.plot(np.correlate(get_val(katzC0),get_val(katzC1)),label='t0-1')
plt.plot(np.correlate(get_val(katzC1),get_val(katzC2)),label='t1-2')
plt.plot(np.correlate(get_val(katzC2),get_val(katzC3)),label='t2-3')
plt.plot(np.correlate(get_val(katzC3),get_val(katzC3)),label='t3-4')
plt.plot(np.correlate(get_val(katzC4),get_val(katzC5)),label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)

```

Out[74]: <matplotlib.legend.Legend at 0x1ada7c6fb38>



```
In [75]: plt.suptitle('Adjacent trace Katz Centrality Fourier Domain convolution p...)
```

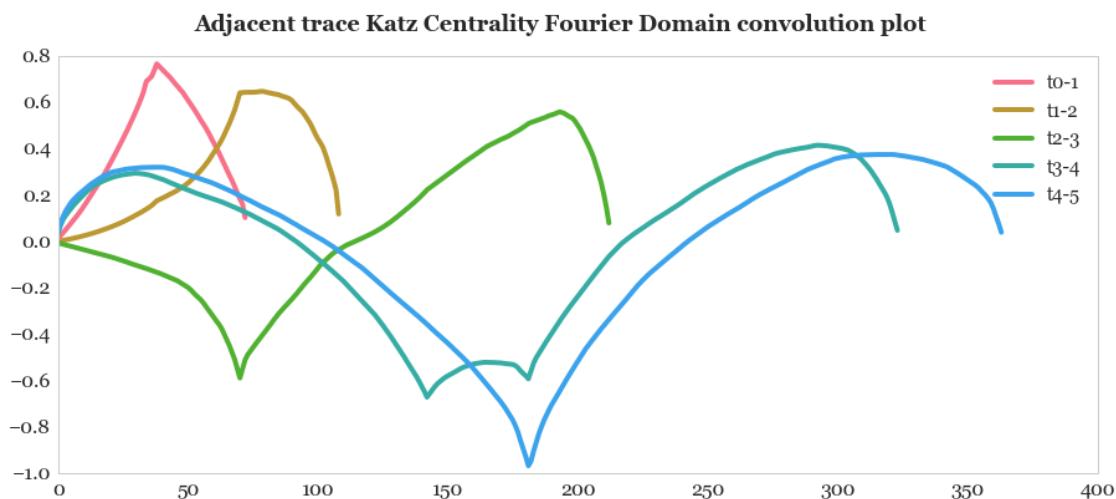
```

plt.plot(fftconvolve(get_val(katzC0), get_val(katzC1)), label='t0-1')
plt.plot(fftconvolve(get_val(katzC1), get_val(katzC2)), label='t1-2')
plt.plot(fftconvolve(get_val(katzC2), get_val(katzC3)), label='t2-3')
plt.plot(fftconvolve(get_val(katzC3), get_val(katzC4)), label='t3-4')
plt.plot(fftconvolve(get_val(katzC4), get_val(katzC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)

```

```
Out[75]: <matplotlib.legend.Legend at 0x1ada7e2d438>
```



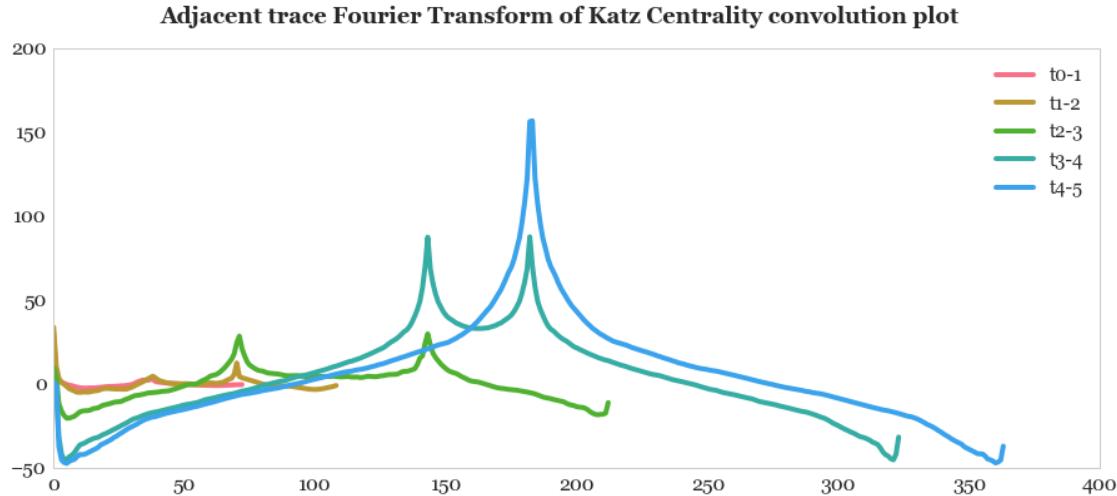
```
In [76]: plt.suptitle('Adjacent trace Fourier Transform of Katz Centrality convolution')

plt.plot(np.convolve(fft_sig(katzC0), fft_sig(katzC1)), label='t0-1')
plt.plot(np.convolve(fft_sig(katzC1), fft_sig(katzC2)), label='t1-2')
plt.plot(np.convolve(fft_sig(katzC2), fft_sig(katzC3)), label='t2-3')
plt.plot(np.convolve(fft_sig(katzC3), fft_sig(katzC4)), label='t3-4')
plt.plot(np.convolve(fft_sig(katzC4), fft_sig(katzC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)

C:\Users\arsha_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:482: ComplexWarning:
return array(a, dtype, copy=False, order=order)
```

Out [76]: <matplotlib.legend.Legend at 0x1ada7ea71d0>



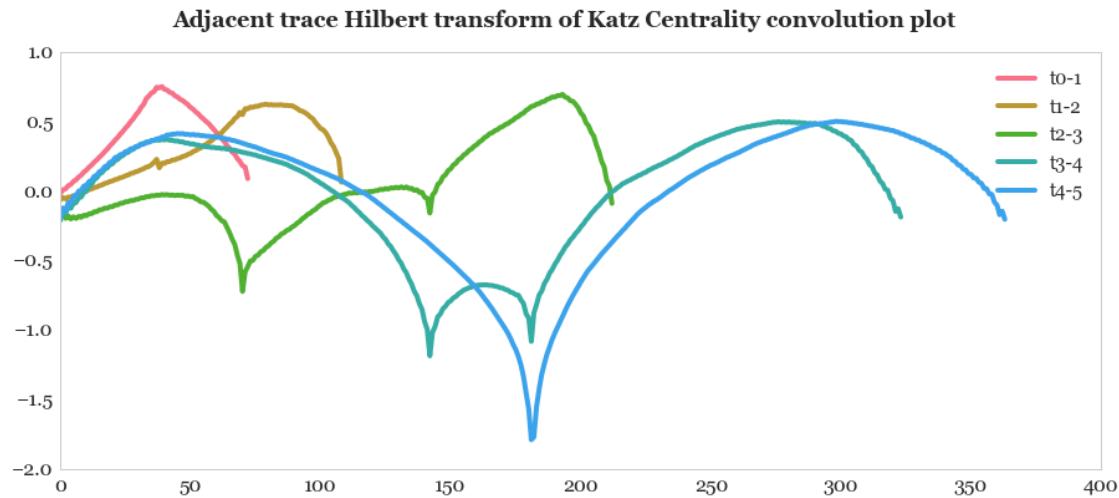
```
In [77]: plt.suptitle('Adjacent trace Hilbert transform of Katz Centrality convolution')

plt.plot(np.convolve(hilbert_sig(katzC0), hilbert_sig(katzC1)), label='t0-1')
plt.plot(np.convolve(hilbert_sig(katzC1), hilbert_sig(katzC2)), label='t1-2')
plt.plot(np.convolve(hilbert_sig(katzC2), hilbert_sig(katzC3)), label='t2-3')
plt.plot(np.convolve(hilbert_sig(katzC3), hilbert_sig(katzC4)), label='t3-4')
plt.plot(np.convolve(hilbert_sig(katzC4), hilbert_sig(katzC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

```
C:\Users\arsha_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:482: ComplexWarning
  return array(a, dtype, copy=False, order=order)
```

```
Out[77]: <matplotlib.legend.Legend at 0x1ada827ee48>
```



### 6.1.8 Load Centrality

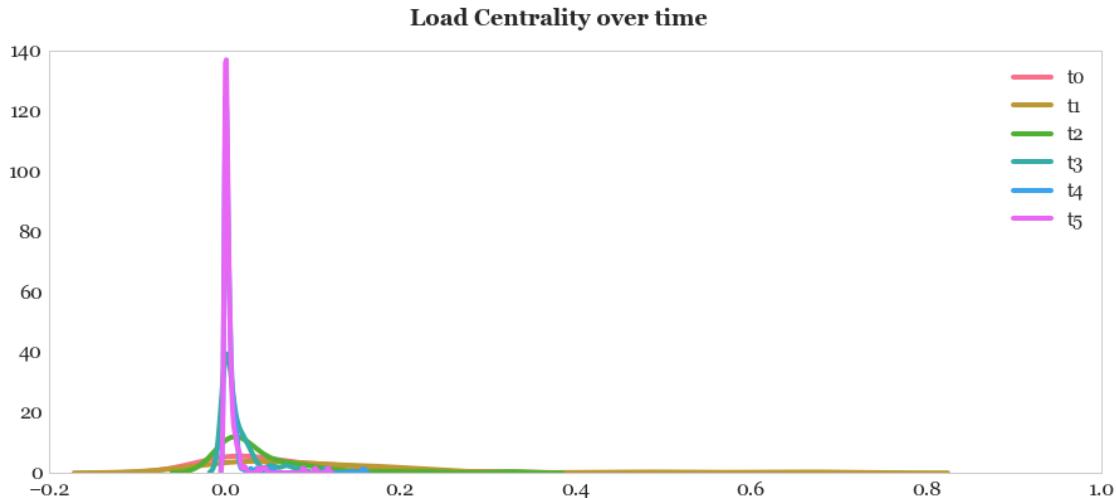
```
In [78]: plt.suptitle('Load Centrality over time', fontsize=18)
```

```
    sns.distplot(get_val(loadC0), hist=False, label='t0')
    sns.distplot(get_val(loadC1), hist=False, label='t1')
    sns.distplot(get_val(loadC2), hist=False, label='t2')
    sns.distplot(get_val(loadC3), hist=False, label='t3')
    sns.distplot(get_val(loadC4), hist=False, label='t4')
    sns.distplot(get_val(loadC5), hist=False, label='t5')

    plt.yticks(fontsize=16)
    plt.xticks(fontsize=16)
    plt.legend(loc=1, fontsize=15)
```

```
C:\Users\arsha_000\Anaconda3\lib\site-packages\statsmodels\nonparametric\kdeutils.py:102: ComplexWarning: Casting float32 to ComplexFloat
  y = X[:m/2+1] + np.r_[0,X[m/2+1:],0]*1j
```

```
Out[78]: <matplotlib.legend.Legend at 0x1ada8453b70>
```



```
In [79]: plt.suptitle('Log Log Plot of Load Centrality over time', fontsize=18)
```

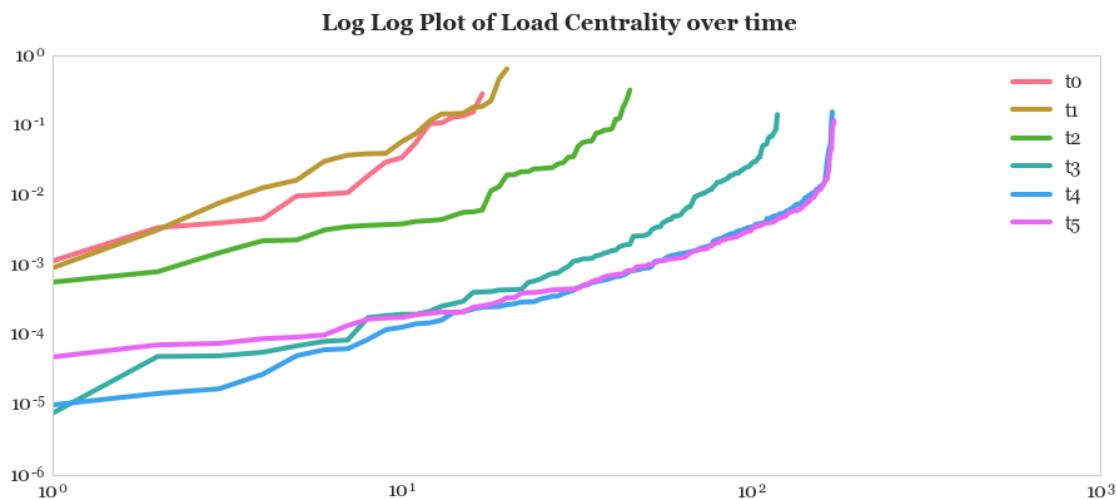
```

plt.loglog(get_val(loadC0), label='t0')
plt.loglog(get_val(loadC1), label='t1')
plt.loglog(get_val(loadC2), label='t2')
plt.loglog(get_val(loadC3), label='t3')
plt.loglog(get_val(loadC4), label='t4')
plt.loglog(get_val(loadC5), label='t5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)

```

```
Out[79]: <matplotlib.legend.Legend at 0x1ada869cdd8>
```

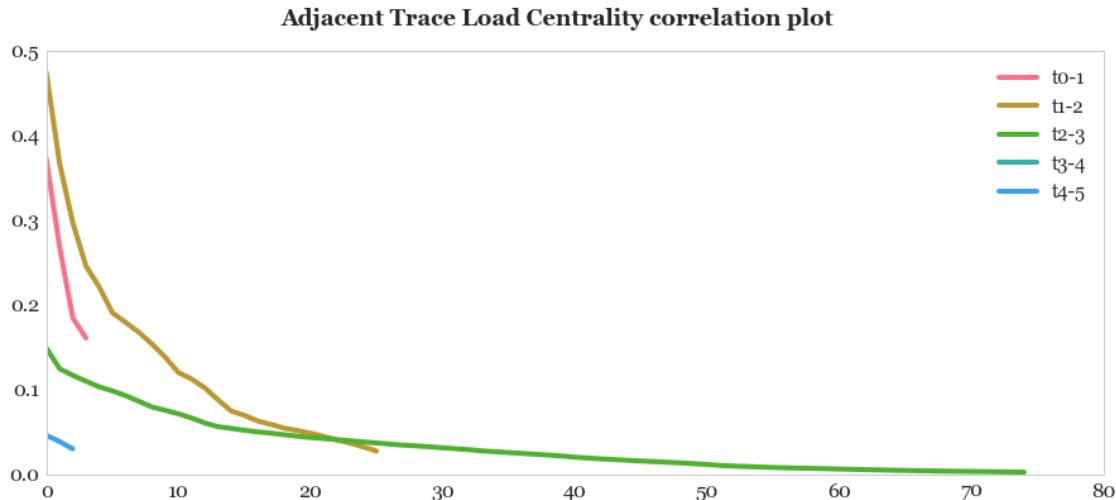


```
In [80]: plt.suptitle('Adjacent Trace Load Centrality correlation plot', fontsize=16)

plt.plot(np.correlate(get_val(loadC0), get_val(loadC1)), label='t0-1')
plt.plot(np.correlate(get_val(loadC1), get_val(loadC2)), label='t1-2')
plt.plot(np.correlate(get_val(loadC2), get_val(loadC3)), label='t2-3')
plt.plot(np.correlate(get_val(loadC3), get_val(loadC4)), label='t3-4')
plt.plot(np.correlate(get_val(loadC4), get_val(loadC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

Out[80]: <matplotlib.legend.Legend at 0x1ada8ab1a90>



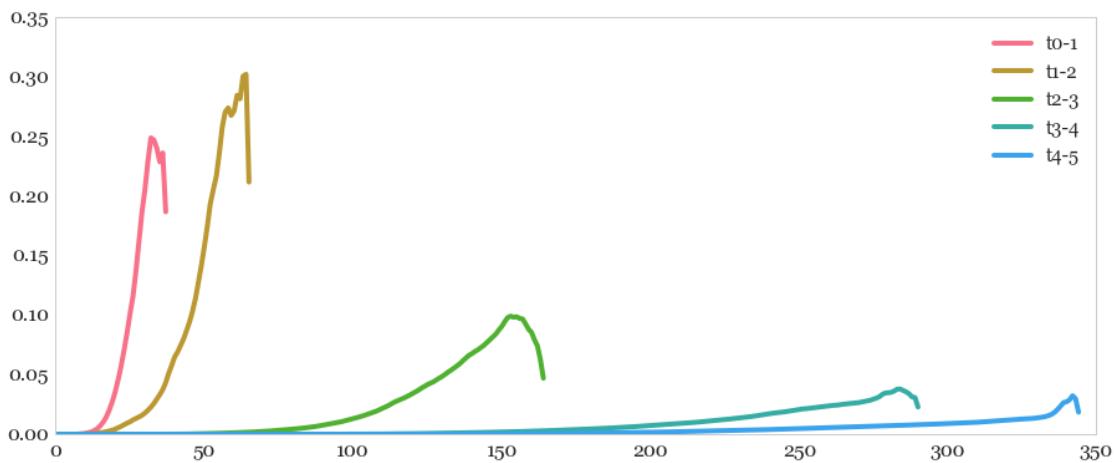
```
In [81]: plt.suptitle('Adjacent trace Load Centrality Fourier Domain convolution plot', fontsize=16)

plt.plot(fftconvolve(get_val(loadC0), get_val(loadC1)), label='t0-1')
plt.plot(fftconvolve(get_val(loadC1), get_val(loadC2)), label='t1-2')
plt.plot(fftconvolve(get_val(loadC2), get_val(loadC3)), label='t2-3')
plt.plot(fftconvolve(get_val(loadC3), get_val(loadC4)), label='t3-4')
plt.plot(fftconvolve(get_val(loadC4), get_val(loadC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

Out[81]: <matplotlib.legend.Legend at 0x1ada8cb6cc0>

**Adjacent trace Load Centrality Fourier Domain convolution plot**



In [82]: plt.suptitle('Adjacent trace Fourier Transform of Load Centrality convolution plot')

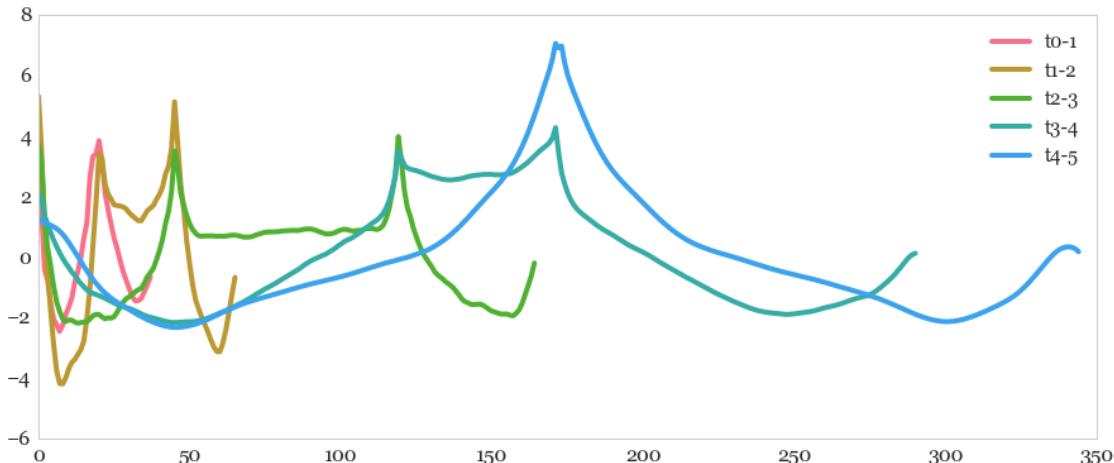
```
plt.plot(np.convolve(fft_sig(loadC0),fft_sig(loadC1)),label='t0-1')
plt.plot(np.convolve(fft_sig(loadC1),fft_sig(loadC2)),label='t1-2')
plt.plot(np.convolve(fft_sig(loadC2),fft_sig(loadC3)),label='t2-3')
plt.plot(np.convolve(fft_sig(loadC3),fft_sig(loadC4)),label='t3-4')
plt.plot(np.convolve(fft_sig(loadC4),fft_sig(loadC5)),label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)
```

C:\Users\arsha\_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:482: ComplexWarning: Casting complex values to real discards the imaginary part
return array(a, dtype, copy=False, order=order)

Out[82]: <matplotlib.legend.Legend at 0x1ada8ec6b70>

**Adjacent trace Fourier Transform of Load Centrality convolution plot**



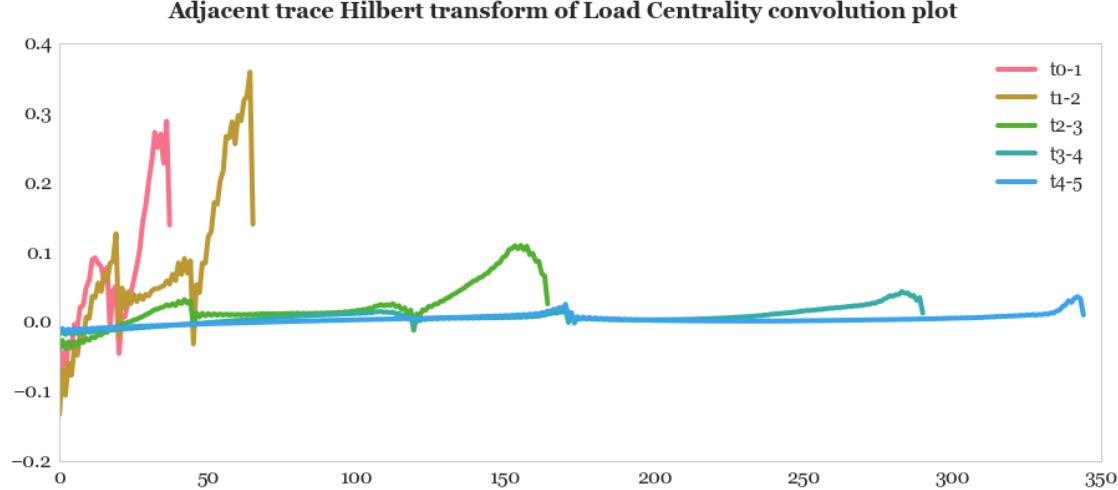
```
In [83]: plt.suptitle('Adjacent trace Hilbert transform of Load Centrality convolution')

plt.plot(np.convolve(hilbert_sig(loadC0), hilbert_sig(loadC1)), label='t0-1')
plt.plot(np.convolve(hilbert_sig(loadC1), hilbert_sig(loadC2)), label='t1-2')
plt.plot(np.convolve(hilbert_sig(loadC2), hilbert_sig(loadC3)), label='t2-3')
plt.plot(np.convolve(hilbert_sig(loadC3), hilbert_sig(loadC4)), label='t3-4')
plt.plot(np.convolve(hilbert_sig(loadC4), hilbert_sig(loadC5)), label='t4-5')

plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(loc=1, fontsize=15)

C:\Users\arsha_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:482: ComplexWarning:
return array(a, dtype, copy=False, order=order)
```

Out[83]: <matplotlib.legend.Legend at 0x1ada8f4ce10>



## 6.2 Centrality Analysis with averaging

### 6.2.1 Calculate Centrality Statistics at different time steps

```
In [84]: deg0, clo0, bet0, eig0, alg0, clust0, commC0, katz0, load0 = cal_stat(Gt0)
deg1, clo1, bet1, eig1, alg1, clust1, commC1, katz1, load1 = cal_stat(Gt1)
deg2, clo2, bet2, eig2, alg2, clust2, commC2, katz2, load2 = cal_stat(Gt2)
deg3, clo3, bet3, eig3, alg3, clust3, commC3, katz3, load3 = cal_stat(Gt3)
deg4, clo4, bet4, eig4, alg4, clust4, commC4, katz4, load4 = cal_stat(Gt4)
deg5, clo5, bet5, eig5, alg5, clust5, commC5, katz5, load5 = cal_stat(Gt5)
```

```
In [85]: print('Avg Deg Cent',deg0)
    print('Avg Clo Cent',clo0)
    print('Avg Bet Cent',bet0)
    print('Avg Eig Cent',eig0)
    print('Avg Alg Connectivity',alg0)
    print('Avg Clustering Coeff',clust0)
    print('Avg Communicability Cent',commC0)
    print('Avg Katz Cent',katz0)
    print('Avg Load Cent', load0)
```

```
Avg Deg Cent 0.018826135105204873
Avg Clo Cent 0.10466121433401401
Avg Bet Cent 0.02598384787834589
Avg Eig Cent 0.07773852412753667
Avg Alg Connectivity 0.0
Avg Clustering Coeff 0.026004228329809725
Avg Communicability Cent 3.9809326044505062
Avg Katz Cent 0.12524033960814704
Avg Load Cent 0.02598384787834589
```

```
In [86]: print('Avg Deg Cent',deg1)
    print('Avg Clo Cent',clo1)
    print('Avg Bet Cent',bet1)
    print('Avg Eig Cent',eig1)
    print('Avg Alg Connectivity',alg1)
    print('Avg Clustering Coeff',clust1)
    print('Avg Communicability Cent',commC1)
    print('Avg Katz Cent',katz1)
```

```
Avg Deg Cent 0.021719858156028365
Avg Clo Cent 0.16550053458700076
Avg Bet Cent 0.05436709836571077
Avg Eig Cent 0.08950640258093145
Avg Alg Connectivity 0.0
Avg Clustering Coeff 0.08708721833721834
Avg Communicability Cent 5.874869893519794
Avg Katz Cent 0.11654349936679959
```

```
In [87]: stat_df = pd.DataFrame([deg0,deg1,deg2,deg3,deg4,deg5])
```

```
In [88]: #calculate density
den0 = nx.density(Gt0)
den1 = nx.density(Gt1)
den2 = nx.density(Gt2)
den3 = nx.density(Gt3)
den4 = nx.density(Gt4)
den5 = nx.density(Gt5)
```

```
In [89]: stat_df['Closeness'] = pd.DataFrame([clo0,clo1,clo2,clo3,clo4,clo5])
stat_df['Betweeness'] = pd.DataFrame([bet0,bet1,bet2,bet3,bet4,bet5])
stat_df['Eig'] = pd.DataFrame([eig0,eig1,eig2,eig3,eig4,eig5])
stat_df['AlgConnect'] = pd.DataFrame([alg0,alg1,alg2,alg3,alg4,alg5])
stat_df['ClustCoeff'] = pd.DataFrame([clust0,clust1,clust2,clust3,clust4,clust5])
stat_df['Communicability'] = pd.DataFrame([commC0,commC1,commC2,commC3,commC4,commC5])
stat_df['Katz'] = pd.DataFrame([katz0,katz1,katz2,katz3,katz4,katz5])
stat_df['Load']=pd.DataFrame([load0,load1,load2,load3,load4,load5])
stat_df['Density'] = pd.DataFrame([den0,den1,den2,den3,den4,den5])
```

```
In [90]: stat_df.columns.values[0]='Deg'
```

```
In [91]: stat_df.head()
```

```
Out[91]:
```

	Deg	Closeness	Betweeness	Eig	AlgConnect	ClustCoeff	\
0	0.018826	0.104661	0.025984	0.077739	0.000000	0.026004	
1	0.021720	0.165501	0.054367	0.089506	0.000000	0.087087	
2	0.020570	0.223937	0.025495	0.066241	0.000000	0.185696	
3	0.031813	0.253585	0.012739	0.056478	0.121915	0.462544	
4	0.047889	0.276022	0.006152	0.058781	0.000000	0.493717	

	Communicability	Katz	Load	Density
0	3.980933e+00	0.125240	0.025984	0.057586
1	5.874870e+00	0.116543	0.054367	0.057624
2	1.206113e+02	0.076152	0.025495	0.054430
3	6.140791e+06	0.011703	0.012739	0.081651
4	1.009380e+12	0.003815	0.006151	0.123401

```
In [92]: stat_df.mean()
```

```
Out[92]:
```

	Deg	Closeness	Betweeness	Eig	AlgConnect	ClustCoeff	Communicability	Katz	Load	Density
	3.167631e-02	2.157075e-01	2.176173e-02	6.800322e-02	2.031923e-02	2.911402e-01	1.302104e+12	5.675227e-02	2.176157e-02	8.438583e-02

```
dtype: float64
```

```
In [93]: stat_df.std()
```

```
Out[93]:
```

	Deg	Closeness	Betweeness	Eig	AlgConnect
	1.384896e-02	6.782144e-02	1.829567e-02	1.307165e-02	4.977175e-02

```

ClustCoeff      2.162089e-01
Communicability 2.725070e+12
Katz            5.646791e-02
Load             1.829584e-02
Density          3.490777e-02
dtype: float64

```

```
In [94]: corr_stat = stat_df.corr()
corr_stat
```

```
Out[94]:
```

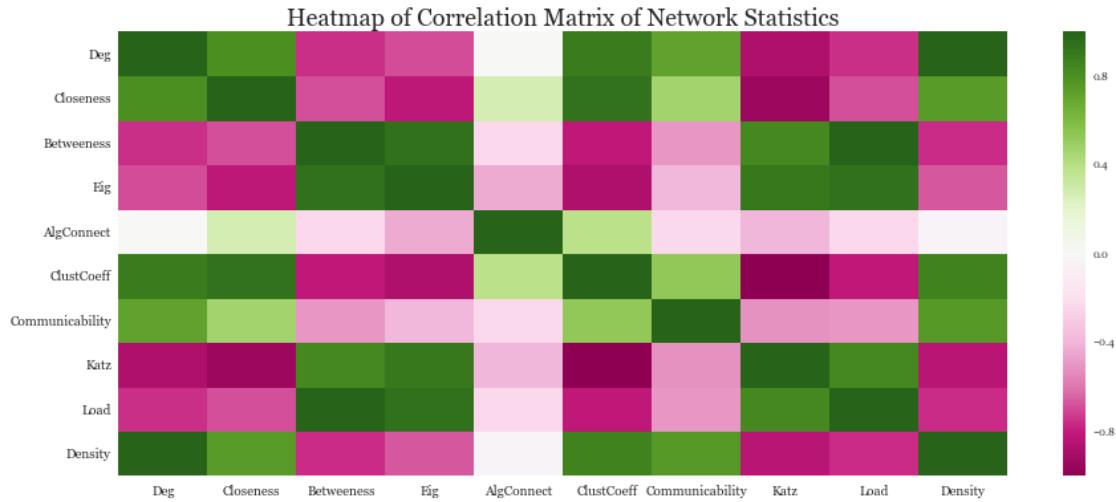
	Deg	Closeness	Betweenness	Eig	AlgConnect	\
Deg	1.000000	0.805217	-0.753366	-0.689411	0.004844	
Closeness	0.805217	1.000000	-0.682081	-0.822651	0.273602	
Betweenness	-0.753366	-0.682081	1.000000	0.938821	-0.241596	
Eig	-0.689411	-0.822651	0.938821	1.000000	-0.431955	
AlgConnect	0.004844	0.273602	-0.241596	-0.431955	1.000000	
ClustCoeff	0.897836	0.934724	-0.812555	-0.875959	0.388376	
Communicability	0.719954	0.469556	-0.497897	-0.385656	-0.234084	
Katz	-0.876722	-0.943750	0.839290	0.910251	-0.390831	
Load	-0.753372	-0.682084	1.000000	0.938820	-0.241589	
Density	0.995111	0.752929	-0.762315	-0.668044	-0.038384	

	ClustCoeff	Communicability	Katz	Load	Density
Deg	0.897836	0.719954	-0.876722	-0.753372	0.995111
Closeness	0.934724	0.469556	-0.943750	-0.682084	0.752929
Betweenness	-0.812555	-0.497897	0.839290	1.000000	-0.762315
Eig	-0.875959	-0.385656	0.910251	0.938820	-0.668044
AlgConnect	0.388376	-0.234084	-0.390831	-0.241589	-0.038384
ClustCoeff	1.000000	0.532793	-0.996347	-0.812557	0.864887
Communicability	0.532793	1.000000	-0.508849	-0.497902	0.758456
Katz	-0.996347	-0.508849	1.000000	0.839292	-0.842771
Load	-0.812557	-0.497902	0.839292	1.000000	-0.762321
Density	0.864887	0.758456	-0.842771	-0.762321	1.000000

```
In [95]: sns.heatmap(corr_stat, cmap='PiYG')
plt.title('Heatmap of Correlation Matrix of Network Statistics', fontsize=14)
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
```

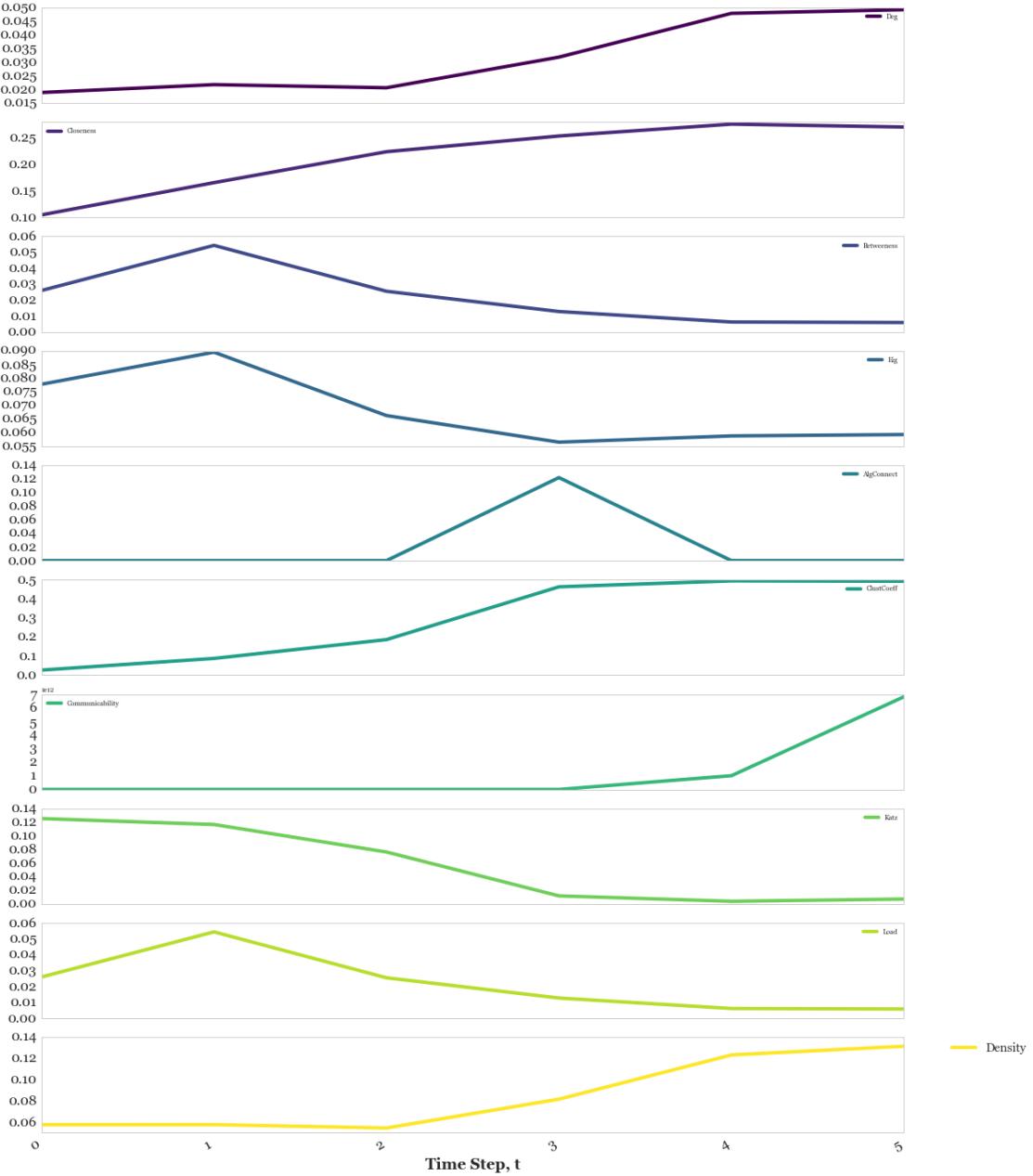
```
Out[95]: (array([ 0.5,  1.5,  2.5,  3.5,  4.5,  5.5,  6.5,  7.5,  8.5,  9.5]),
 <a list of 10 Text yticklabel objects>)
```



```
In [163]: stat_df.plot(colormap='viridis', fontsize=16, subplots=True, figsize=(18, 10))
plt.suptitle('Plot of Network Statistics', fontsize=20)
plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(fontsize=14, bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0)
plt.xlabel("Time Step, t", fontsize=18)
```

```
Out[163]: <matplotlib.text.Text at 0x1adc8471eb8>
```

Plot of Network Statistics



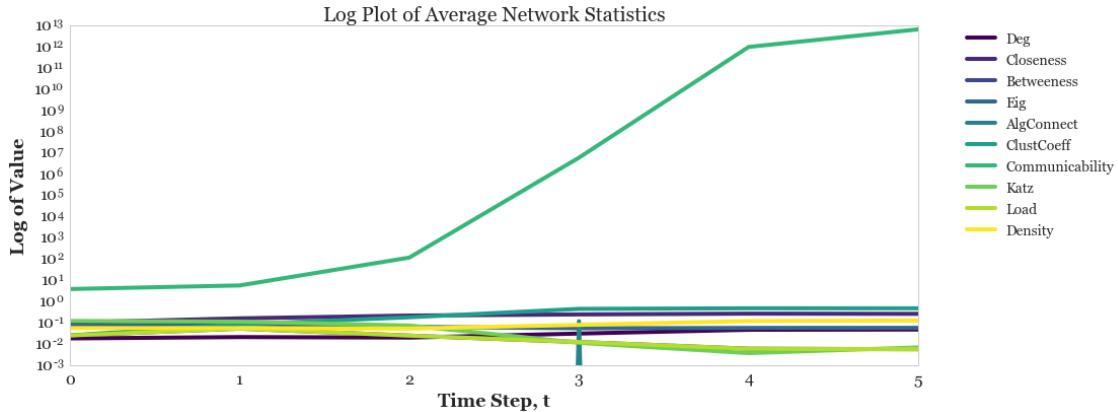
```
In [97]: stat_df.plot(colormap='viridis', logy=True, fontsize=14)
plt.title('Log Plot of Average Network Statistics', fontsize=20)
plt.yticks(fontsize=16)
plt.xticks(fontsize=16)
plt.legend(fontsize=14, bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
```

```

plt.xlabel("Time Step, t", fontsize=18)
plt.ylabel("Log of Value", fontsize=18)

```

Out[97]: <matplotlib.text.Text at 0x1ada53571d0>



## 7 Assortativity Analysis

```

In [98]: def cal_assort_att(net):
    dac = nx.degree_assortativity_coefficient(net)
    dpc = nx.degree_pearson_correlation_coefficient(net)
    avg_neigdeg = nx.average_neighbor_degree(net)
    avg_degconnect = nx.average_degree_connectivity(net)
    triangles = nx.triangles(net)

    return [dac, dpc, avg_neigdeg, avg_degconnect, triangles]

```

In [99]: dac0 = nx.degree\_assortativity\_coefficient(Gt0)

In [100]: nx.degree\_pearson\_correlation\_coefficient(Gt0)

Out[100]: -0.25126403290770427

### 7.1 Calculate Assortativity statistics for each time step

```

In [101]: dac0,dpc0,avg_neigdeg0, avg_degconnect0, triangles0= cal_assort_att(Gt0)
          dac1,dpc1,avg_neigdeg1, avg_degconnect1, triangles1= cal_assort_att(Gt1)
          dac2,dpc2,avg_neigdeg2, avg_degconnect2, triangles2= cal_assort_att(Gt2)
          dac3,dpc3,avg_neigdeg3, avg_degconnect3, triangles3= cal_assort_att(Gt3)
          dac4,dpc4,avg_neigdeg4, avg_degconnect4, triangles4= cal_assort_att(Gt4)
          dac5,dpc5,avg_neigdeg5, avg_degconnect5, triangles5= cal_assort_att(Gt5)

```

In [102]: avg\_cent(avg\_neigdeg0)

```
Out[102]: 2.190131186642814
```

```
In [103]: assor_df = pd.DataFrame([dac0,dac1,dac2,dac3,dac4,dac5])
assor_df['DegPearCC'] = pd.DataFrame([dpc0,dpc1,dpc2,dpc3,dpc4,dpc5])
```

```
In [104]: assor_df['Avg (AvgNeighDeg)'] = pd.DataFrame([avg_cent(avg_neigdeg0),avg_
avg_cent(avg_neigdeg2),avg_
avg_cent(avg_neigdeg4), avg_
```

```
In [105]: assor_df['Avg (AvgDegConnect)'] = pd.DataFrame([avg_cent(avg_degconnect0),
avg_cent(avg_degconnect2),avg_
avg_cent(avg_degconnect4), avg_
```

```
In [106]: assor_df['AvgTriangles'] = pd.DataFrame([avg_cent(triangles0),avg_cent(tri_
avg_cent(triangles2),avg_cen_
avg_cent(triangles4), avg_ce
```

```
In [107]: assor_df.columns.values[0]= 'DegAssorCoeff'
assor_df
```

```
Out[107]:    DegAssorCoeff  DegPearCC  Avg (AvgNeighDeg)  Avg (AvgDegConnect) \
0      -0.251264   -0.251264        2.190131          3.600092
1      -0.226108   -0.226108        2.896955          4.906208
2      -0.178525   -0.178525        5.563177          9.037252
3       0.074870    0.074870       16.332357         17.412081
4      -0.040770   -0.040770       31.159027         32.211278
5      -0.046592   -0.046592       32.873515         34.366099

           AvgTriangles
0            0.023256
1            0.125000
2            2.762500
3           28.272727
4          104.180328
5          116.304348
```

```
In [108]: stat_df2 = assor_df.join(stat_df)
```

```
In [109]: stat_df2.head()
```

```
Out[109]:    DegAssorCoeff  DegPearCC  Avg (AvgNeighDeg)  Avg (AvgDegConnect) \
0      -0.251264   -0.251264        2.190131          3.600092
1      -0.226108   -0.226108        2.896955          4.906208
2      -0.178525   -0.178525        5.563177          9.037252
3       0.074870    0.074870       16.332357         17.412081
4      -0.040770   -0.040770       31.159027         32.211278

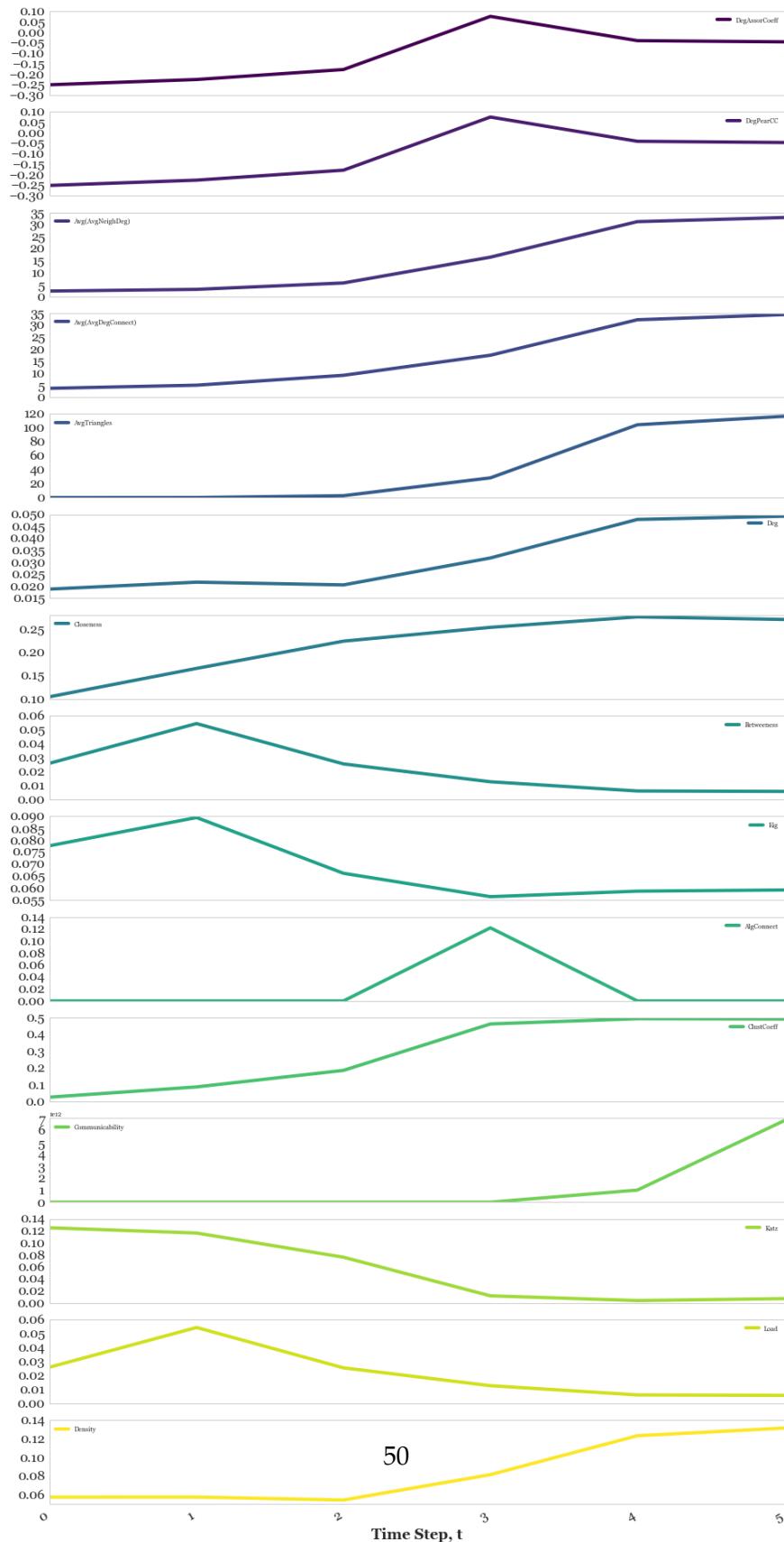
           AvgTriangles      Deg  Closeness  Betweenness      Eig  AlgConnect \
0            0.023256  0.018826    0.104661     0.025984  0.077739  0.000000
```

1	0.125000	0.021720	0.165501	0.054367	0.089506	0.000000
2	2.762500	0.020570	0.223937	0.025495	0.066241	0.000000
3	28.272727	0.031813	0.253585	0.012739	0.056478	0.121915
4	104.180328	0.047889	0.276022	0.006152	0.058781	0.000000
	ClustCoeff	Communicability	Katz	Load	Density	
0	0.026004	3.980933e+00	0.125240	0.025984	0.057586	
1	0.087087	5.874870e+00	0.116543	0.054367	0.057624	
2	0.185696	1.206113e+02	0.076152	0.025495	0.054430	
3	0.462544	6.140791e+06	0.011703	0.012739	0.081651	
4	0.493717	1.009380e+12	0.003815	0.006151	0.123401	

```
In [168]: stat_df2.plot(colormap='viridis', figsize=(16,36), fontsize=16, sharex=True)
plt.suptitle('Plot of Individual Average Network Statistics', fontsize=20)
# plt.legend(fontsize=14, bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0)
plt.xlabel("Time Step, t", fontsize=18)
# plt.ylabel("Log of Value", fontsize=18)
```

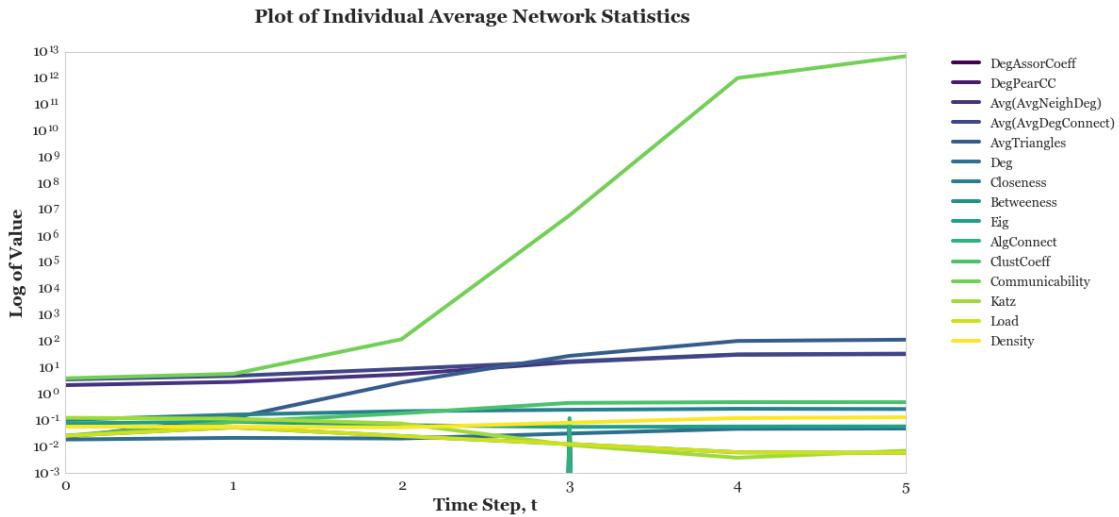
```
Out[168]: <matplotlib.text.Text at 0x1adcb3ae278>
```

**Plot of Individual Average Network Statistics**



```
In [110]: stat_df2.plot(colormap='viridis', figsize=(16,8), fontsize=16, sharex=True
plt.suptitle('Plot of Individual Average Network Statistics', fontsize=20)
plt.legend(fontsize=14, bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0)
plt.xlabel("Time Step, t", fontsize=18)
plt.ylabel("Log of Value", fontsize=18)
```

Out[110]: <matplotlib.text.Text at 0x1adaab3f6d8>



```
In [111]: stat_df2.describe()
```

```
Out[111]:      DegAssorCoeff  DegPearCC  Avg (AvgNeighDeg)  Avg (AvgDegConnect)  \
count    6.000000   6.000000    6.000000    6.000000
mean    -0.111398  -0.111398  15.169194  16.922168
std     0.127366  0.127366  14.012924  13.581757
min    -0.251264  -0.251264  2.190131  3.600092
25%    -0.214212  -0.214212  3.563511  5.938969
50%    -0.112558  -0.112558  10.947767  13.224666
75%    -0.042225  -0.042225  27.452360  28.511479
max     0.074870   0.074870  32.873515  34.366099

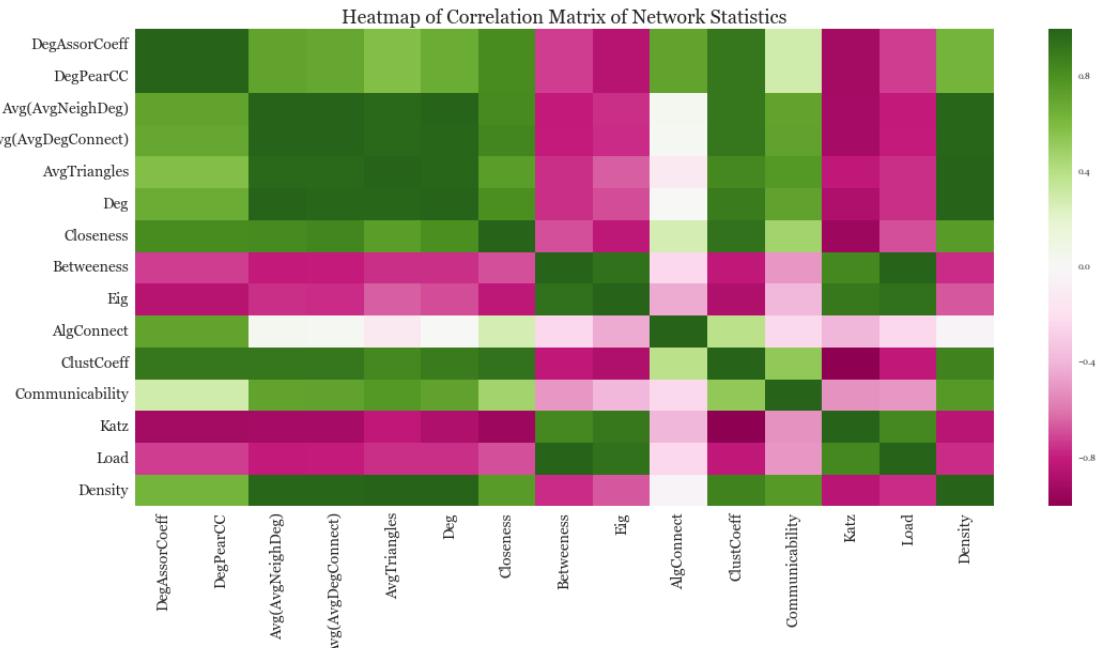
          AvgTriangles  Deg  Closeness  Betweenness  Eig  AlgConnect
count    6.000000   6.000000  6.000000  6.000000  6.000000  6.000000
mean    41.944693  0.031676  0.215707  0.021762  0.068003  0.020312
std     54.094534  0.013849  0.067821  0.018296  0.013072  0.049771
min     0.023256  0.018826  0.104661  0.005834  0.056478  0.000000
25%    0.784375  0.020857  0.180110  0.007798  0.058904  0.000000
50%    15.517614  0.026767  0.238761  0.019117  0.062758  0.000000
```

75%	85.203428	0.043870	0.266301	0.025862	0.074864	0.00000
max	116.304348	0.049240	0.276022	0.054367	0.089506	0.12191

	ClustCoeff	Communicability	Katz	Load	Density
count	6.000000	6.000000e+00	6.000000	6.000000	6.000000
mean	0.291140	1.302104e+12	0.056752	0.021762	0.084386
std	0.216209	2.725070e+12	0.056468	0.018296	0.034908
min	0.026004	3.980933e+00	0.003815	0.005833	0.054430
25%	0.111739	3.455898e+01	0.008220	0.007798	0.057595
50%	0.324120	3.070456e+06	0.043928	0.019117	0.069637
75%	0.484481	7.570362e+11	0.106446	0.025862	0.112964
max	0.493717	6.803237e+12	0.125240	0.054367	0.131623

```
In [112]: plt.figure(figsize=(18,8))
sns.heatmap(stat_df2.corr(), cmap='PiYG')
plt.title('Heatmap of Correlation Matrix of Network Statistics', fontsize=14)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
```

```
Out[112]: (array([ 0.5, 1.5, 2.5, 3.5, 4.5, 5.5, 6.5, 7.5, 8.5,
       9.5, 10.5, 11.5, 12.5, 13.5, 14.5]), <a list of 15 Text yticklabel objects>)
```



## 8 Graph Spectra

### 8.1 Modularity Matrix

```
In [113]: modM0 = nx.modularity_matrix(Gt0)
          modM1 = nx.modularity_matrix(Gt1)
          modM2 = nx.modularity_matrix(Gt2)
          modM3 = nx.modularity_matrix(Gt3)
          modM4 = nx.modularity_matrix(Gt4)
          modM5 = nx.modularity_matrix(Gt5)

In [114]: plt.figure(figsize=(64, 42))

          plt.subplot(231)
          sns.heatmap(modM0, cmap='Greys')
          plt.suptitle('Heatmap of Modularity Matrix, t0-t5', fontsize=80)

          plt.subplot(232)
          sns.heatmap(modM1, cmap='Greys')

          plt.subplot(233)
          sns.heatmap(modM2, cmap='Greys')

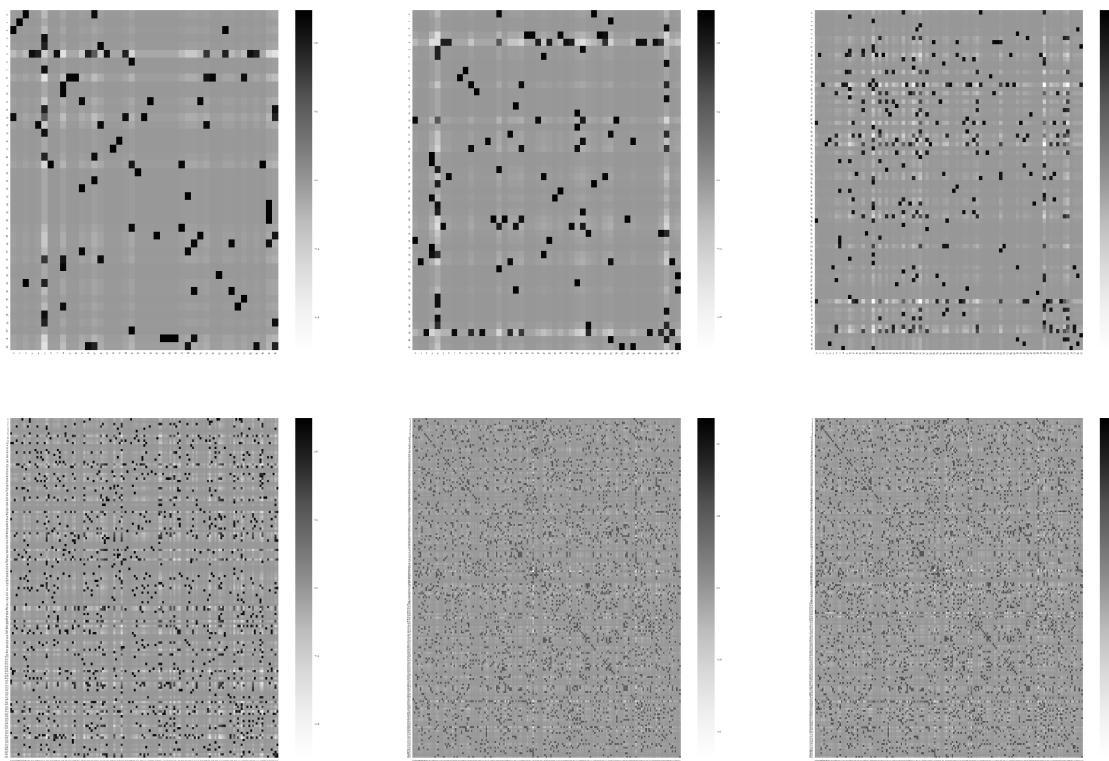
          plt.subplot(234)
          sns.heatmap(modM3, cmap='Greys')

          plt.subplot(235)
          sns.heatmap(modM4, cmap='Greys')

          plt.subplot(236)
          sns.heatmap(modM5, cmap='Greys')

Out[114]: <matplotlib.axes._subplots.AxesSubplot at 0x1adaa62d198>
```

**Heatmap of Modularity Matrix, to-t5**



## 8.2 Laplacian Matrix

```
In [115]: lapM0 = nx.laplacian_matrix(Gt0).todense()
          lapM1 = nx.laplacian_matrix(Gt1).todense()
          lapM2 = nx.laplacian_matrix(Gt2).todense()
          lapM3 = nx.laplacian_matrix(Gt3).todense()
          lapM4 = nx.laplacian_matrix(Gt4).todense()
          lapM5 = nx.laplacian_matrix(Gt5).todense()

In [116]: plt.figure(figsize=(64, 42))

          plt.subplot(231)
          sns.heatmap(lapM0, cmap='Greys')
          plt.suptitle('Heatmap of Laplacian Matrix, t0-t5', fontsize=80)

          plt.subplot(232)
          sns.heatmap(lapM1, cmap='Greys')

          plt.subplot(233)
          sns.heatmap(lapM2, cmap='Greys')
```

```

plt.subplot(234)
sns.heatmap(lapM3, cmap='Greys')

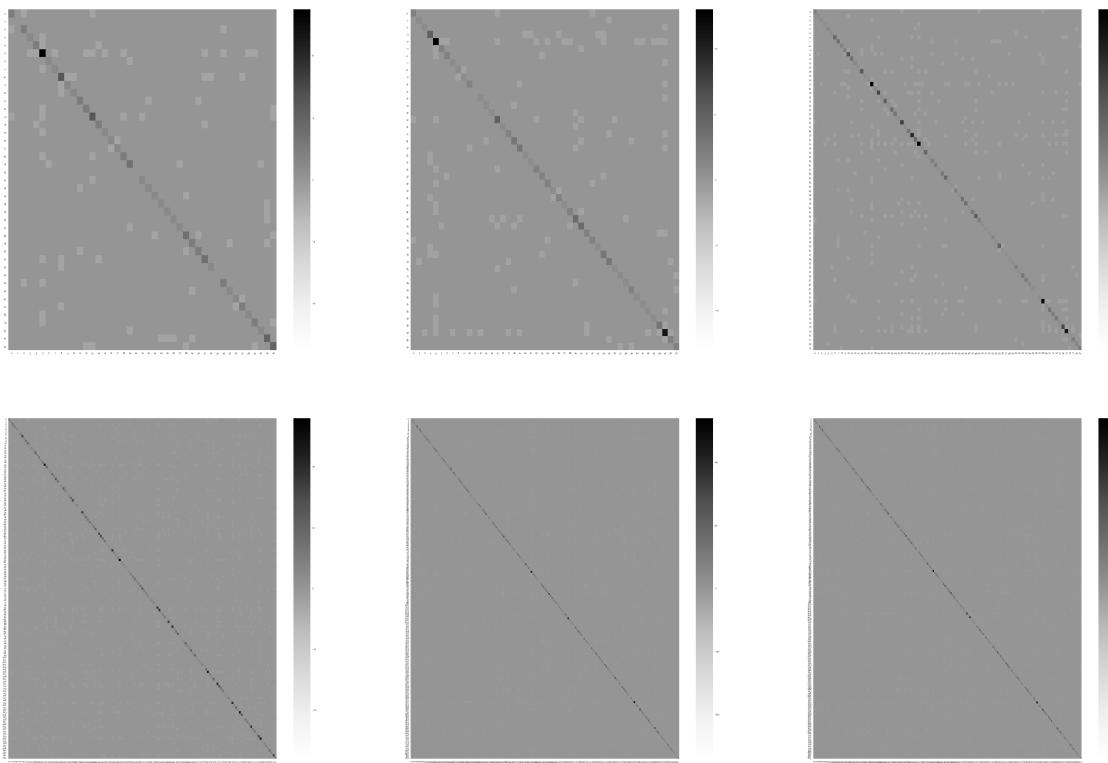
plt.subplot(235)
sns.heatmap(lapM4, cmap='Greys')

plt.subplot(236)
sns.heatmap(lapM5, cmap='Greys')

```

Out[116]: <matplotlib.axes.\_subplots.AxesSubplot at 0x1adade1d7f0>

**Heatmap of Laplacian Matrix, to-t5**



### 8.3 Adjacency Matrix

```

In [117]: adjM0 = nx.adjacency_matrix(Gt0).todense()
adjM1 = nx.adjacency_matrix(Gt1).todense()
adjM2 = nx.adjacency_matrix(Gt2).todense()
adjM3 = nx.adjacency_matrix(Gt3).todense()
adjM4 = nx.adjacency_matrix(Gt4).todense()
adjM5 = nx.adjacency_matrix(Gt5).todense()

```

In [118]: plt.figure(figsize=(64, 42))

```

plt.subplot(231)
sns.heatmap(adjM0, cmap='Greys')
plt.suptitle('Heatmap of Adjacency Matrix, t0-t5', fontsize=80)

plt.subplot(232)
sns.heatmap(adjM1, cmap='Greys')

plt.subplot(233)
sns.heatmap(adjM2, cmap='Greys')

plt.subplot(234)
sns.heatmap(adjM3, cmap='Greys')

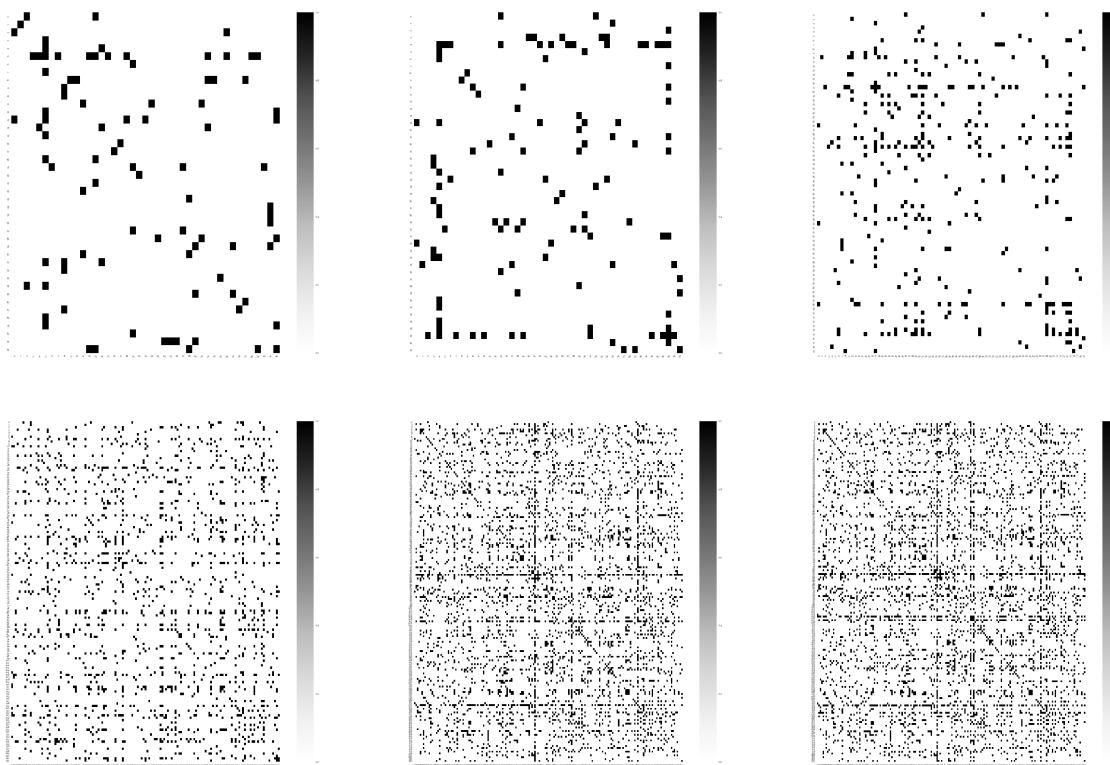
plt.subplot(235)
sns.heatmap(adjM4, cmap='Greys')

plt.subplot(236)
sns.heatmap(adjM5, cmap='Greys')

```

Out[118]: <matplotlib.axes.\_subplots.AxesSubplot at 0x1adb972d898>

**Heatmap of Adjacency Matrix, to-t5**



## 8.4 Incidence Matrix

```
In [119]: incM0 = nx.incidence_matrix(Gt0).todense()
incM1 = nx.incidence_matrix(Gt1).todense()
incM2 = nx.incidence_matrix(Gt2).todense()
incM3 = nx.incidence_matrix(Gt3).todense()
incM4 = nx.incidence_matrix(Gt4).todense()
incM5 = nx.incidence_matrix(Gt5).todense()

In [120]: plt.figure(figsize=(64, 42))

plt.subplot(231)
sns.heatmap(incM0, cmap='Greys')
plt.suptitle('Heatmap of Incidence Matrix, t0-t5', fontsize=80)

plt.subplot(232)
sns.heatmap(incM1, cmap='Greys')

plt.subplot(233)
sns.heatmap(incM2, cmap='Greys')

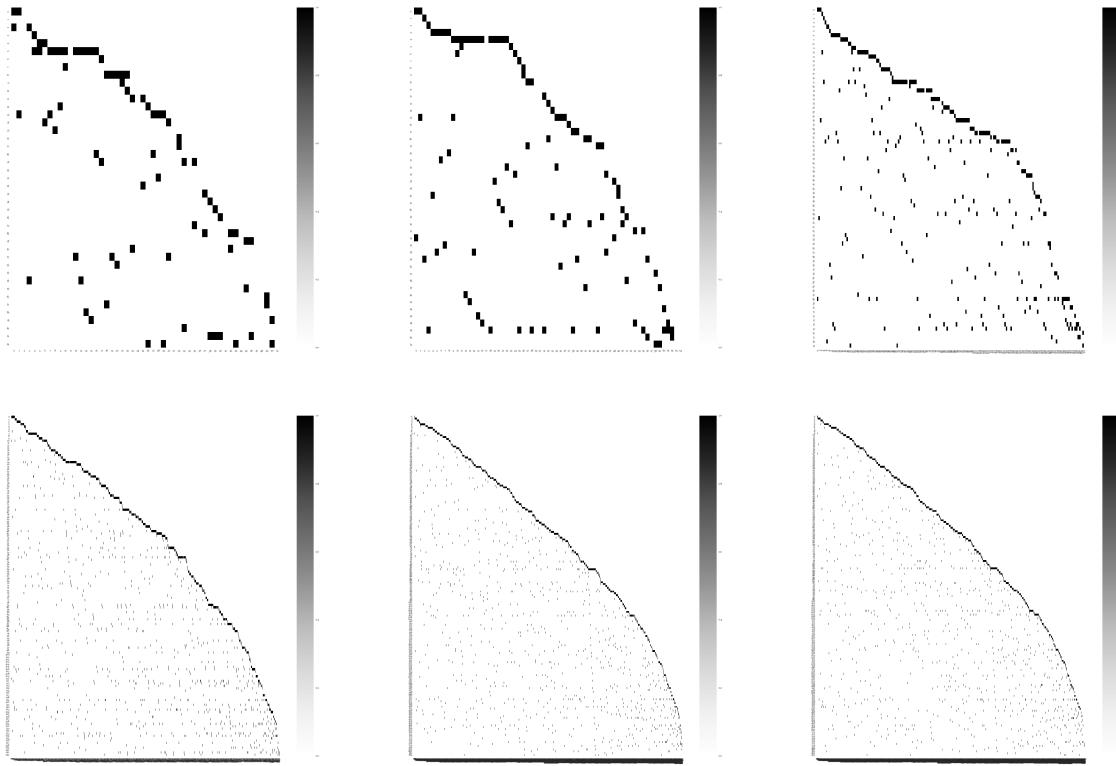
plt.subplot(234)
sns.heatmap(incM3, cmap='Greys')

plt.subplot(235)
sns.heatmap(incM4, cmap='Greys')

plt.subplot(236)
sns.heatmap(incM5, cmap='Greys')

Out[120]: <matplotlib.axes._subplots.AxesSubplot at 0x1adb7e95c88>
```

**Heatmap of Incidence Matrix, to-t5**



## 9 Subgraph Stationarity

The subgraph stationarity is computed in 2 steps.

**Step 1:**

Compute

$$Ct = \frac{A(t0) \cap A(t0 + 1)}{A(t0) \cup A(t0 + 1)}$$

This is effectively the autocorrelation of the graph with a time delayed version of itself.

$A(t)$  denotes the adjacency matrix

**Step 2:**

Calculate Subgraph stationarity,  $\zeta$

$$\zeta = \frac{\sum_{t=0}^{tmax-1} C(t, t + 1)}{tmax - t0 - 1}$$

```
In [121]: def pad_shape(x, ref, offset=0):
    result = np.zeros_like(ref)
    result[0:x.shape[0]+offset, 0:x.shape[1]+offset] = x

    return [result, nx.Graph(result)]
```

```
In [122]: _,Gt0_pad = pad_shape(adjM0,adjM1)
Gt0_int_Gt0= Gt0.copy()
Gt0_int_Gt0.remove_nodes_from(n for n in Gt0 if n not in Gt0)
Gt0_U_Gt0 = nx.disjoint_union(Gt0,Gt0)
adjmat_inter = nx.adjacency_matrix(Gt0_int_Gt0).todense()
adjmat_union = nx.adjacency_matrix(Gt0_U_Gt0).todense()
adjmat_inter_pad,_ = pad_shape(adjmat_inter,adjmat_union)
Ct0 = np.divide(np.linalg.norm(adjmat_inter_pad),np.linalg.norm(adjmat_union))
Ct0
```

Out[122]: 0.70710678118654757

```
In [123]: _,Gt0_pad = pad_shape(adjM0,adjM1)
Gt0_int_Gt1= Gt0.copy()
Gt0_int_Gt1.remove_nodes_from(n for n in Gt0 if n not in Gt1)
Gt0_U_Gt1 = nx.disjoint_union(Gt0_pad,Gt1)
adjmat_inter = nx.adjacency_matrix(Gt0_int_Gt1).todense()
adjmat_union = nx.adjacency_matrix(Gt0_U_Gt1).todense()
adjmat_inter_pad,_ = pad_shape(adjmat_inter,adjmat_union)
Ct1 = np.divide(np.linalg.norm(adjmat_inter_pad),np.linalg.norm(adjmat_union))
Ct1
```

Out[123]: 0.66232865352709824

```
In [124]: _,Gt1_pad = pad_shape(adjM1,adjM2)
Gt1_int_Gt2= Gt1.copy()
Gt1_int_Gt2.remove_nodes_from(n for n in Gt1 if n not in Gt2)
Gt1_U_Gt2 = nx.disjoint_union(Gt0_pad,Gt1)
adjmat_inter = nx.adjacency_matrix(Gt1_int_Gt2).todense()
adjmat_union = nx.adjacency_matrix(Gt1_U_Gt2).todense()
adjmat_inter_pad,_ = pad_shape(adjmat_inter,adjmat_union)
Ct2 = np.divide(np.linalg.norm(adjmat_inter_pad),np.linalg.norm(adjmat_union))
Ct2
```

Out[124]: 0.7492134240101288

```
In [125]: _,Gt2_pad = pad_shape(adjM2,adjM3)
Gt2_int_Gt3= Gt2.copy()
Gt2_int_Gt3.remove_nodes_from(n for n in Gt3 if n not in Gt3)
Gt2_U_Gt3 = nx.disjoint_union(Gt2_pad,Gt3)
adjmat_inter = nx.adjacency_matrix(Gt2_int_Gt3).todense()
adjmat_union = nx.adjacency_matrix(Gt2_U_Gt3).todense()
adjmat_inter_pad,_ = pad_shape(adjmat_inter,adjmat_union)
Ct3 = np.divide(np.linalg.norm(adjmat_inter_pad),np.linalg.norm(adjmat_union))
Ct3
```

Out[125]: 0.41226013627128677

```
In [126]: _,Gt3_pad = pad_shape(adjM3,adjM4)
Gt3_int_Gt4= Gt3.copy()
```

```

Gt3_int_Gt4.remove_nodes_from(n for n in Gt3 if n not in Gt4)
Gt3_U_Gt4 = nx.disjoint_union(Gt3_pad,Gt4)
adjmat_inter = nx.adjacency_matrix(Gt3_int_Gt4).todense()
adjmat_union = nx.adjacency_matrix(Gt3_U_Gt4).todense()
adjmat_inter_pad,_ = pad_shape(adjmat_inter,adjmat_union)
Ct4 = np.divide(np.linalg.norm(adjmat_inter_pad),np.linalg.norm(adjmat_union))
Ct4

```

Out [126]: 0.53425969593338996

```

In [127]: _,Gt4_pad = pad_shape(adjM4,adjM5)
Gt4_int_Gt5= Gt1.copy()
Gt4_int_Gt5.remove_nodes_from(n for n in Gt4 if n not in Gt5)
Gt4_U_Gt5 = nx.disjoint_union(Gt4_pad,Gt5)
adjmat_inter = nx.adjacency_matrix(Gt4_int_Gt5).todense()
adjmat_union = nx.adjacency_matrix(Gt4_U_Gt5).todense()
adjmat_inter_pad,_ = pad_shape(adjmat_inter,adjmat_union)
Ct5 = np.divide(np.linalg.norm(adjmat_inter_pad),np.linalg.norm(adjmat_union))
Ct5

```

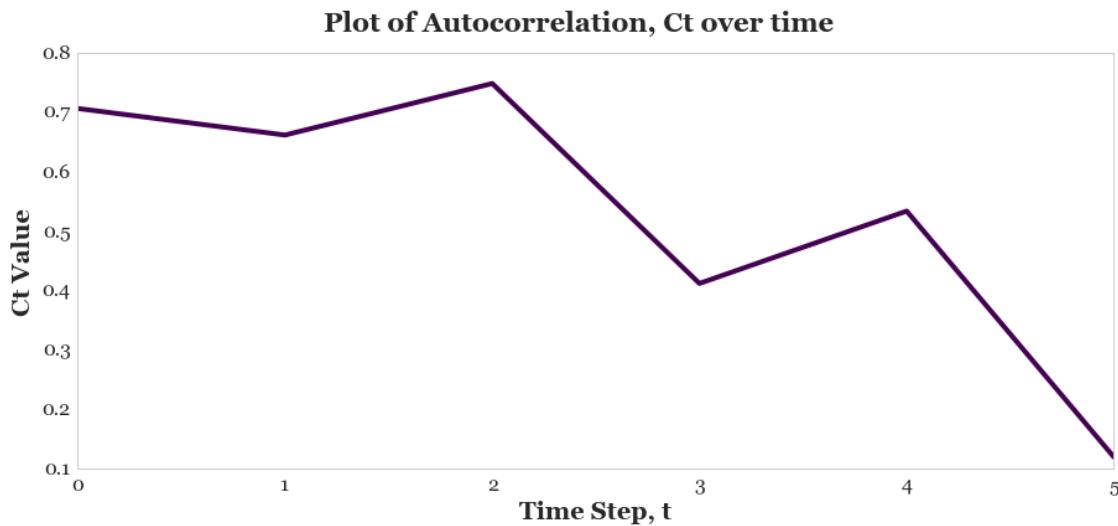
Out [127]: 0.11965940514762706

```

In [128]: Ct_df = pd.DataFrame([Ct0,Ct1,Ct2,Ct3,Ct4,Ct5])
Ct_df.plot(fontsize=16, cmap='viridis', legend=False)
plt.suptitle('Plot of Autocorrelation, Ct over time', fontsize=22)
plt.xlabel("Time Step, t", fontsize=20)
plt.ylabel("Ct Value", fontsize=20)

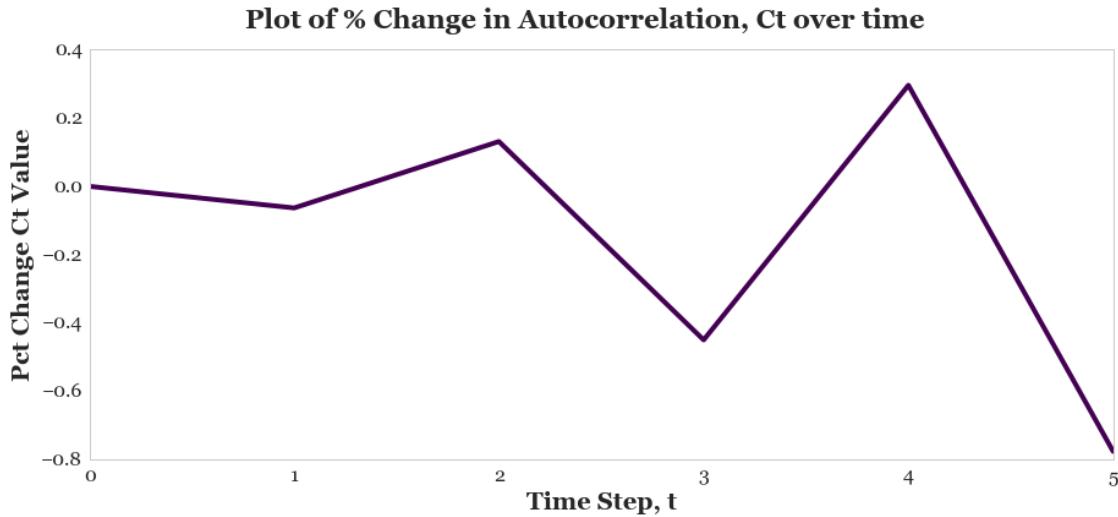
```

Out [128]: <matplotlib.text.Text at 0x1adc6f96320>



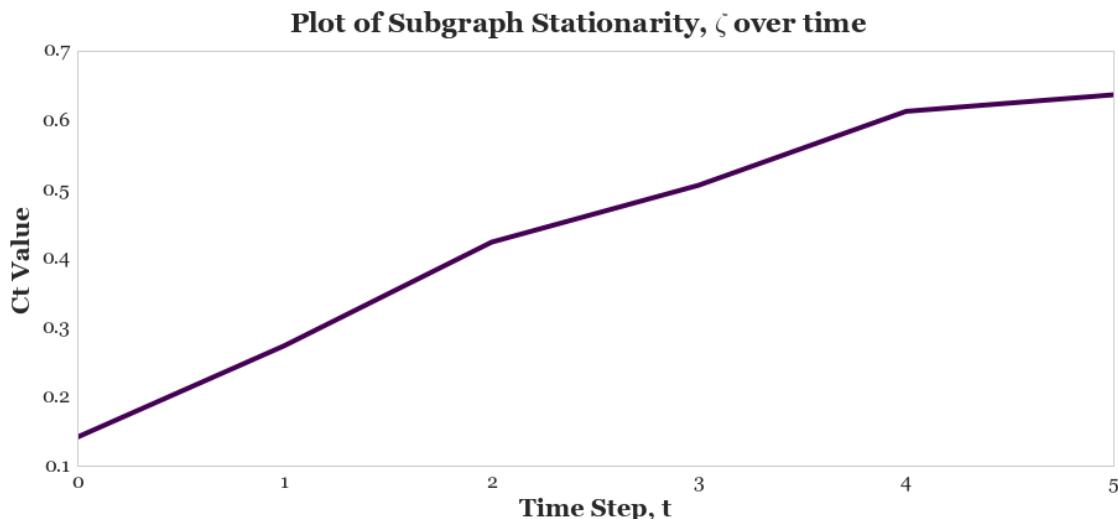
```
In [129]: Ct_df.pct_change().fillna(0).plot(fontsize=16, cmap='viridis', legend=False)
plt.suptitle('Plot of % Change in Autocorrelation, Ct over time', fontsize=20)
plt.xlabel("Time Step, t", fontsize=20)
plt.ylabel("Pct Change Ct Value", fontsize=20)
```

```
Out[129]: <matplotlib.text.Text at 0x1adc6cd6128>
```



```
In [130]: zeta = Ct_df.cumsum() / (5)
zeta.plot(fontsize=16, cmap='viridis', legend=False)
plt.suptitle('Plot of Subgraph Stationarity, $\zeta$ over time', fontsize=20)
plt.xlabel("Time Step, t", fontsize=20)
plt.ylabel("Ct Value", fontsize=20)
```

```
Out[130]: <matplotlib.text.Text at 0x1adc6be0f60>
```



```
In [131]: zeta.mad()

Out[131]: 0      0.152857
           dtype: float64
```

## 10 Graph Stationarity Ratio

The stationarity ratio as used here is inspired by the [Matlab Code](#) based on the arXiv:1601.02522

```
In [132]: def stationarity_ratio(G):
    #stationarity ratio with laplian
    L = nx.laplacian_matrix(G).todense()
    U = nx.laplacian_spectrum(G)
    C = np.cov(L)
    CF = np.dot(L, np.dot(np.dot(U.T, C), U))
    r = np.linalg.norm(np.diag(CF)) / np.linalg.norm(CF)

    #stationarity with modularity
    M = nx.modularity_matrix(G)
    U_mod = nx.modularity_spectrum(G)
    C_mod = np.cov(M)
    CF_mod = np.dot(M, np.dot(np.dot(U_mod.T, C_mod), U_mod))
    r_mod = np.linalg.norm(np.diag(CF_mod)) / np.linalg.norm(CF_mod)

    #adjacency matrix stationarity
    A = nx.incidence_matrix(G).todense()
    U_adj = nx.adjacency_spectrum(G)
    C_adj = np.cov(A)
    CF_adj = np.dot(A, np.dot(np.dot(U_adj.T, C_adj), U_adj))
    r_adj = np.linalg.norm(np.diag(CF_adj)) / np.linalg.norm(CF_adj)

    return [r, r_mod, r_adj]
```

```
In [133]: st_rat0, mod_st_rat0, adj_st_rat0 = stationarity_ratio(Gt0)
st_rat1, mod_st_rat1, adj_st_rat1 = stationarity_ratio(Gt1)
st_rat2, mod_st_rat2, adj_st_rat2 = stationarity_ratio(Gt2)
st_rat3, mod_st_rat3, adj_st_rat3 = stationarity_ratio(Gt3)
st_rat4, mod_st_rat4, adj_st_rat4 = stationarity_ratio(Gt4)
st_rat5, mod_st_rat5, adj_st_rat5 = stationarity_ratio(Gt5)
```

```
In [134]: stationarity_df = pd.DataFrame([st_rat0, st_rat1, st_rat2, st_rat3, st_rat4, st_rat5])
stationarity_df['ModStatRat'] = pd.DataFrame([mod_st_rat0, mod_st_rat1, mod_st_rat2, mod_st_rat3, mod_st_rat4, mod_st_rat5])
stationarity_df['AdjStatRat'] = pd.DataFrame([adj_st_rat0, adj_st_rat1, adj_st_rat2, adj_st_rat3, adj_st_rat4, adj_st_rat5])
```

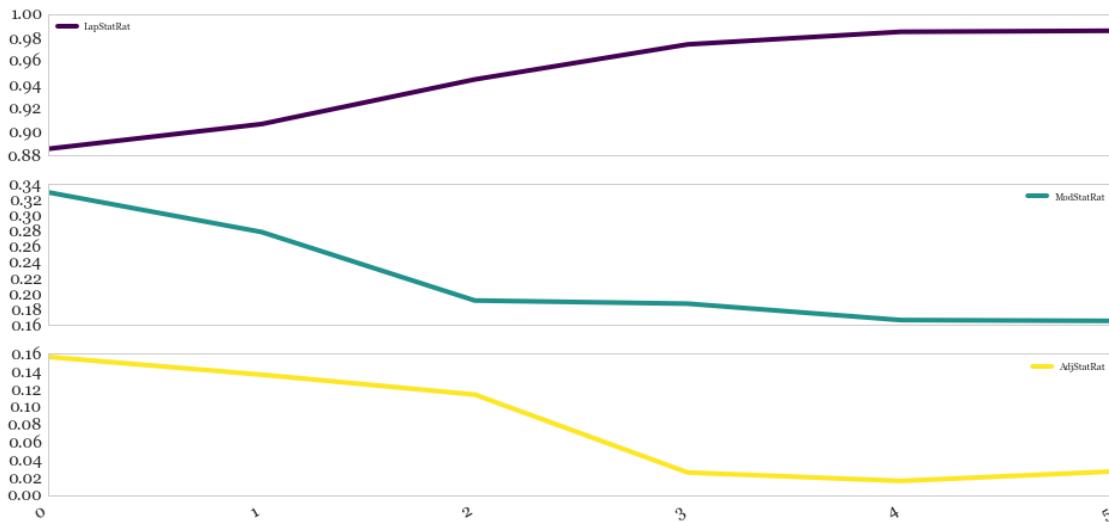
```
In [135]: stationarity_df.columns.values[0]='LapStatRat'  
stationarity_df
```

```
Out[135]:   LapStatRat  ModStatRat  AdjStatRat  
0      0.885557    0.328867    0.156174  
1      0.906522    0.278447    0.136083  
2      0.944330    0.191400    0.113592  
3      0.974044    0.187360    0.025516  
4      0.984701    0.166550    0.016042  
5      0.985587    0.165496    0.026745
```

```
In [169]: stationarity_df.plot(subplots=True, fontsize=14, legend=True, sharex=True)  
plt.suptitle('Plot of Graph Stationarity Ratio from 3 graph matrices', fo
```

```
Out[169]: <matplotlib.text.Text at 0x1adcb56d6d8>
```

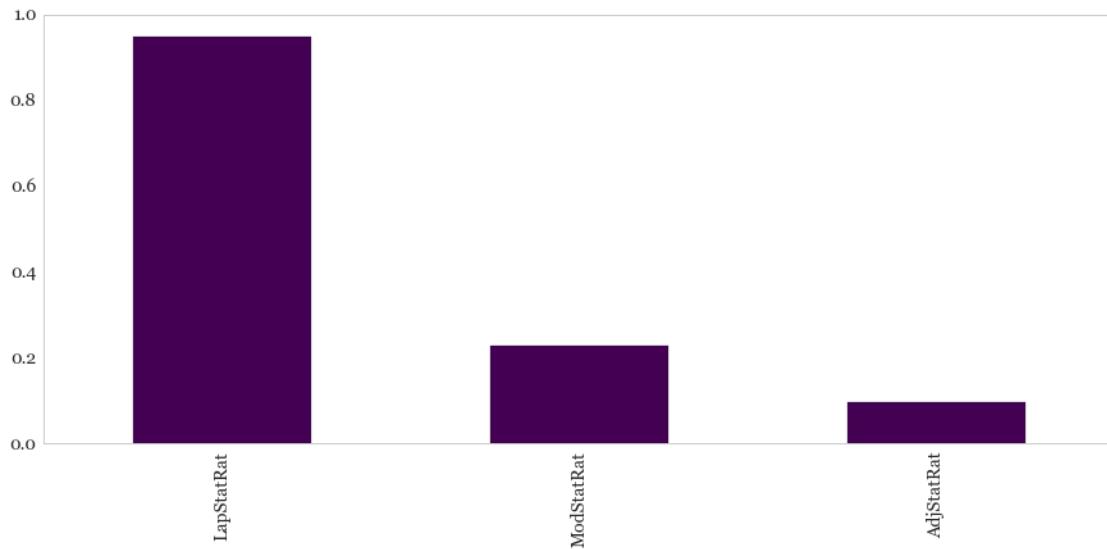
**Plot of Graph Stationarity Ratio from 3 graph matrices**



```
In [171]: stationarity_df.apply(rms).plot(kind='bar', fontsize=14, colormap='viridis')  
plt.suptitle('RMS of Stationarity Ratio for 3 Matrices', fontsize=18)
```

```
Out[171]: <matplotlib.text.Text at 0x1adcbdb2390>
```

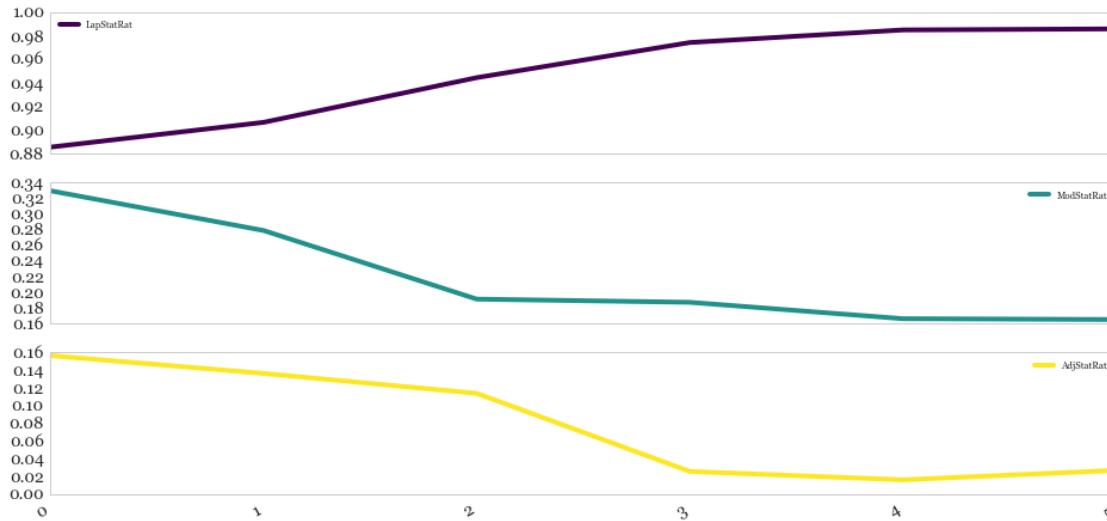
**RMS of Stationarity Ratio for 3 Matrices**



```
In [172]: stationarity_df.apllymap(rms).plot(subplots=True, fontsize=14, legend=True)
plt.suptitle('Plot of RMS of Graph Stationarity Ratio from 3 graph matrices')
```

```
Out[172]: <matplotlib.text.Text at 0x1adcb9af518>
```

**Plot of RMS of Graph Stationarity Ratio from 3 graph matrices**



```
In [139]: Nrms_df = pd.DataFrame([nrms(st_rat0,st_rat1), nrms(st_rat1,st_rat2),
                                 nrms(st_rat4,st_rat5)])
```

```
In [140]: Nrms_df['AdjNrms'] = pd.DataFrame([0,nrms(adj_st_rat0,adj_st_rat1), nrms(adj_st_rat2,adj_st_rat3), nrms(adj_st_rat4,adj_st_rat5)])
```

```
In [141]: Nrms_df['ModNrms'] = pd.DataFrame([0,nrms(mod_st_rat0,mod_st_rat1), nrms(mod_st_rat2,mod_st_rat3), nrms(mod_st_rat4,mod_st_rat5)])
```

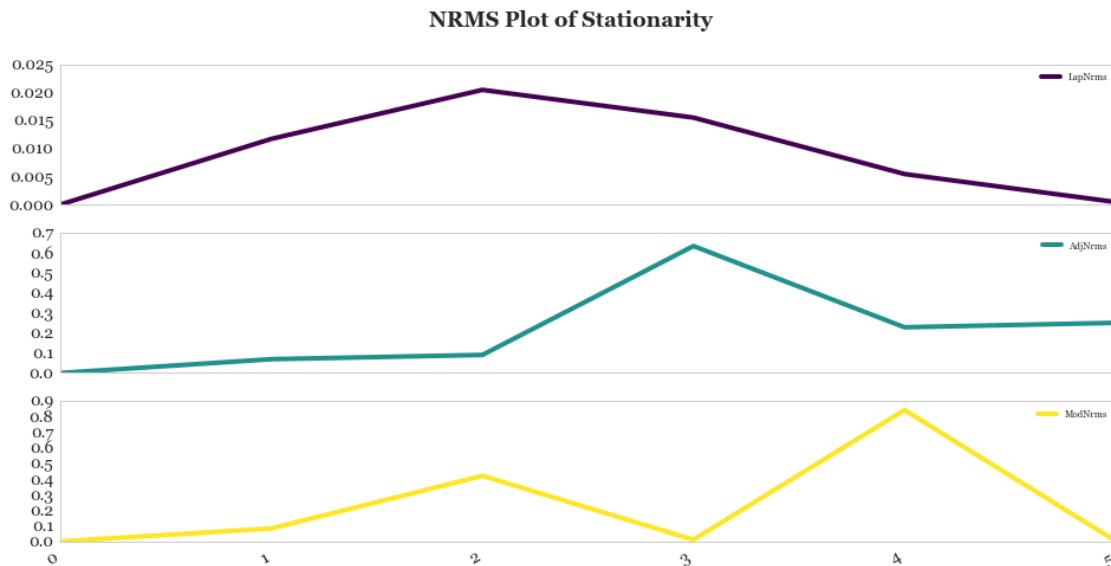
```
In [142]: Nrms_df.columns.values[0]='LapNrms'
```

```
In [143]: Nrms_df
```

```
Out[143]:   LapNrms    AdjNrms    ModNrms
0  0.000000  0.000000  0.000000
1  0.011699  0.068744  0.083020
2  0.020428  0.090079  0.420506
3  0.015489  0.633155  0.010667
4  0.005441  0.227972  0.842266
5  0.000450  0.250161  0.003174
```

```
In [144]: Nrms_df.plot(subplots=True, fontsize=14, legend=True, sharex=True, figsize=(10, 10))
plt.suptitle('NRMS Plot of Stationarity', fontsize=18)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
#plt.legend(fontsize=14, bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0)
```

```
Out[144]: (array([ 0.,  0.1,  0.2,  0.3,  0.4,  0.5,  0.6,  0.7,  0.8,  0.9]),  
<a list of 10 Text yticklabel objects>)
```



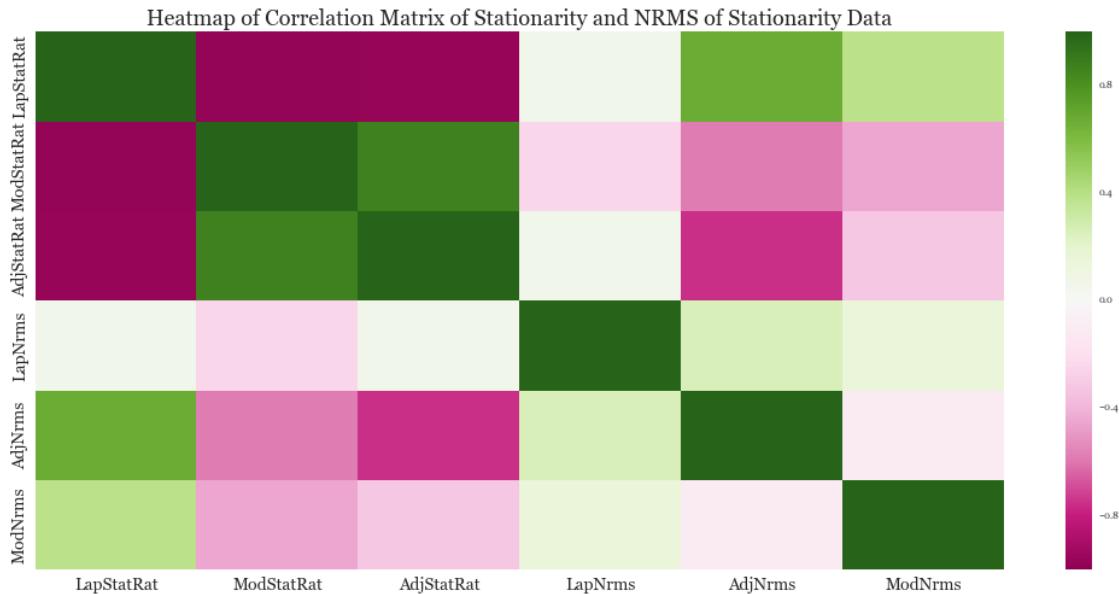
```
In [145]: stat_df3= stationarity_df.join(Nrms_df)
```

```
In [146]: stat_df3.head()
```

```
Out[146]:    LapStatRat  ModStatRat  AdjStatRat  LapNrms  AdjNrms  ModNrms
0      0.885557  0.328867  0.156174  0.000000  0.000000  0.000000
1      0.906522  0.278447  0.136083  0.011699  0.068744  0.083020
2      0.944330  0.191400  0.113592  0.020428  0.090079  0.420506
3      0.974044  0.187360  0.025516  0.015489  0.633155  0.010667
4      0.984701  0.166550  0.016042  0.005441  0.227972  0.842266
```

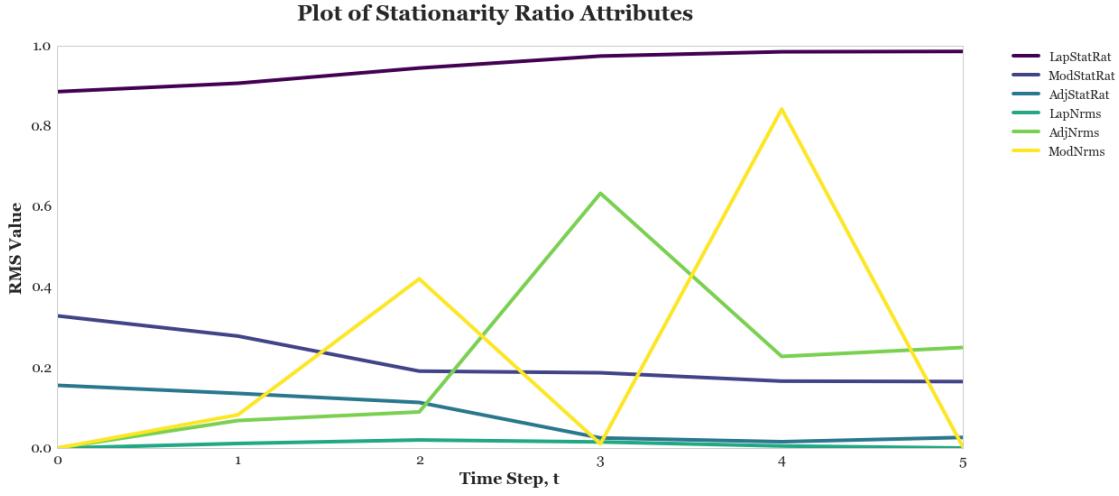
```
In [147]: plt.figure(figsize=(18,8))
sns.heatmap(stat_df3.corr(), cmap='PiYG')
plt.title('Heatmap of Correlation Matrix of Stationarity and NRMS of Stationarity Data')
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
```

```
Out[147]: (array([ 0.5,  1.5,  2.5,  3.5,  4.5,  5.5]),
<a list of 6 Text yticklabel objects>)
```



```
In [217]: stat_df3.plot(colormap='viridis', figsize=(18,8), fontsize=14)
plt.suptitle('Plot of Stationarity Ratio Attributes', fontsize=24)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.xlabel("Time Step, t", fontsize=18)
plt.ylabel("RMS Value", fontsize=18)
plt.legend(fontsize=14, bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0)
```

```
Out[217]: <matplotlib.legend.Legend at 0x1addc861e10>
```



## 11 Frequency Wavenumber Plots, F-k

The Fourier Transform of a timeseries gives its frequency components.

The Wavenumber, k is defined as

$$\kappa = \frac{1}{frequency}$$

Essentially we expect to see the signal in a central cone and the noise distributed around it.

```
In [149]: lap_spec0 = nx.laplacian_spectrum(Gt0)
           mod_spec0 = nx.modularity_spectrum(Gt0)
           adj_spec0 = nx.adjacency_spectrum(Gt0)

           lap_spec1 = nx.laplacian_spectrum(Gt1)
           mod_spec1= nx.modularity_spectrum(Gt1)
           adj_spec1= nx.adjacency_spectrum(Gt1)

           lap_spec2 = nx.laplacian_spectrum(Gt2)
           mod_spec2= nx.modularity_spectrum(Gt2)
           adj_spec2= nx.adjacency_spectrum(Gt2)

           lap_spec3 = nx.laplacian_spectrum(Gt3)
           mod_spec3= nx.modularity_spectrum(Gt3)
           adj_spec3= nx.adjacency_spectrum(Gt3)

           lap_spec4 = nx.laplacian_spectrum(Gt4)
           mod_spec4= nx.modularity_spectrum(Gt4)
           adj_spec4= nx.adjacency_spectrum(Gt4)

           lap_spec5 = nx.laplacian_spectrum(Gt5)
```

```

mod_spec5= nx.modularity_spectrum(Gt5)
adj_spec5= nx.adjacency_spectrum(Gt5)

In [150]: def fk_plot(f,name):
    freq = sc.fft(f)
    wavnum = 1/freq

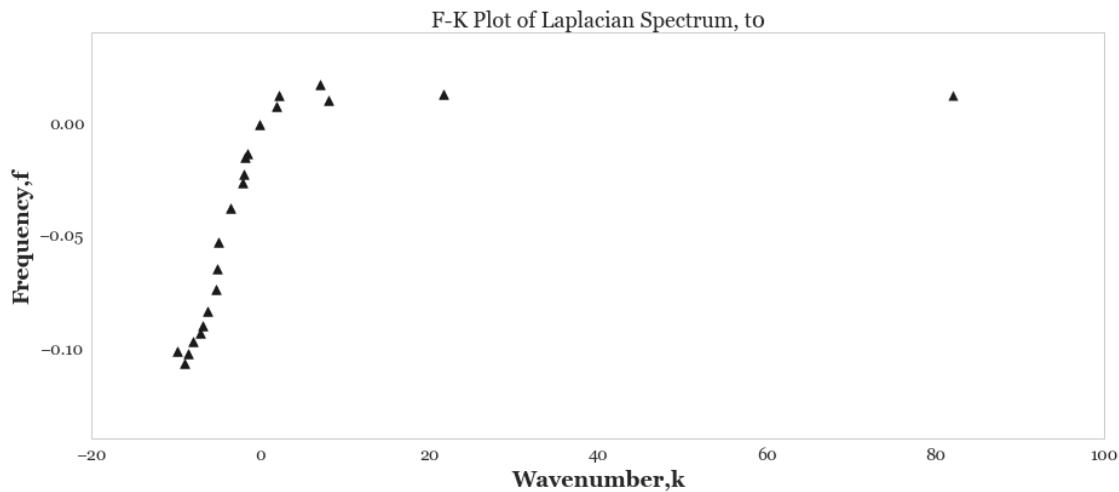
    plt.scatter(freq, wavnum, s=60, marker='^', c='k')
    plt.title("F-K Plot of "+str(name), fontsize=18)
    plt.xticks(fontsize=14)
    plt.yticks(fontsize=14)
    plt.xlabel("Wavenumber,k", fontsize=18)
    plt.ylabel("Frequency,f", fontsize=18)
    plt.show()

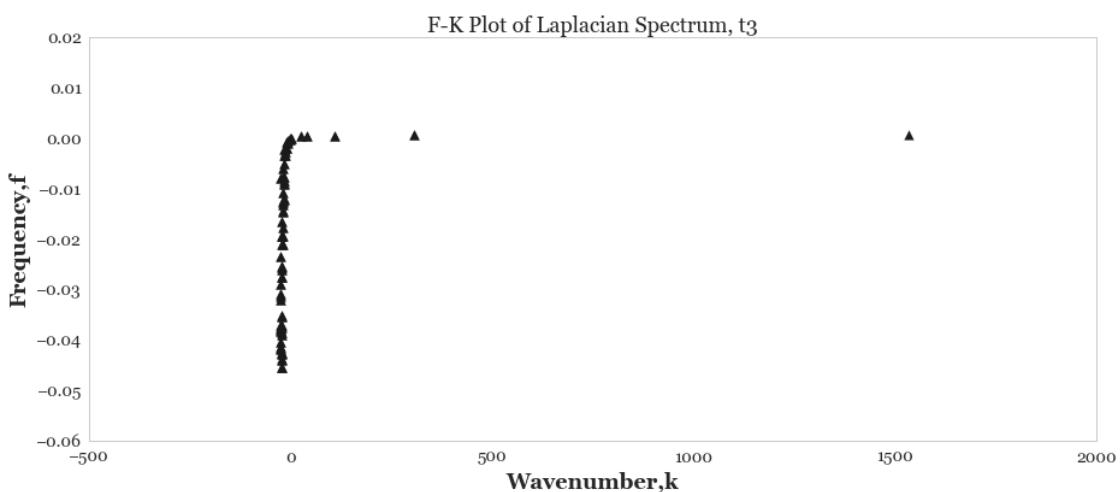
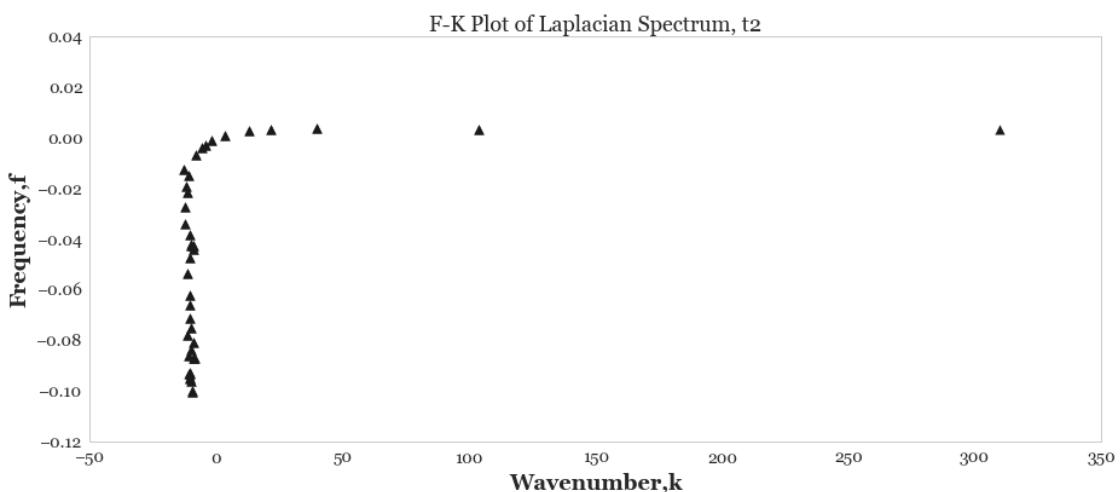
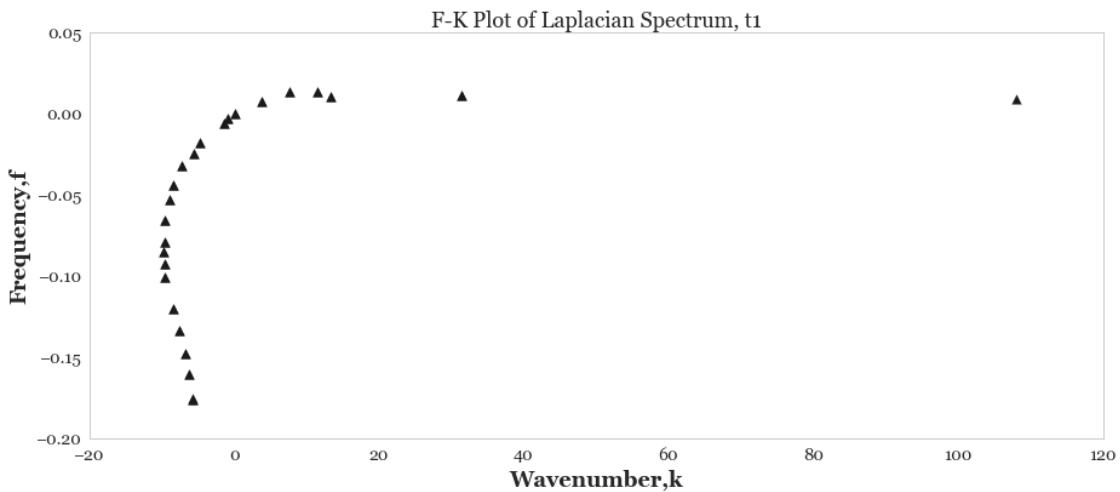
    return [freq,wavnum]

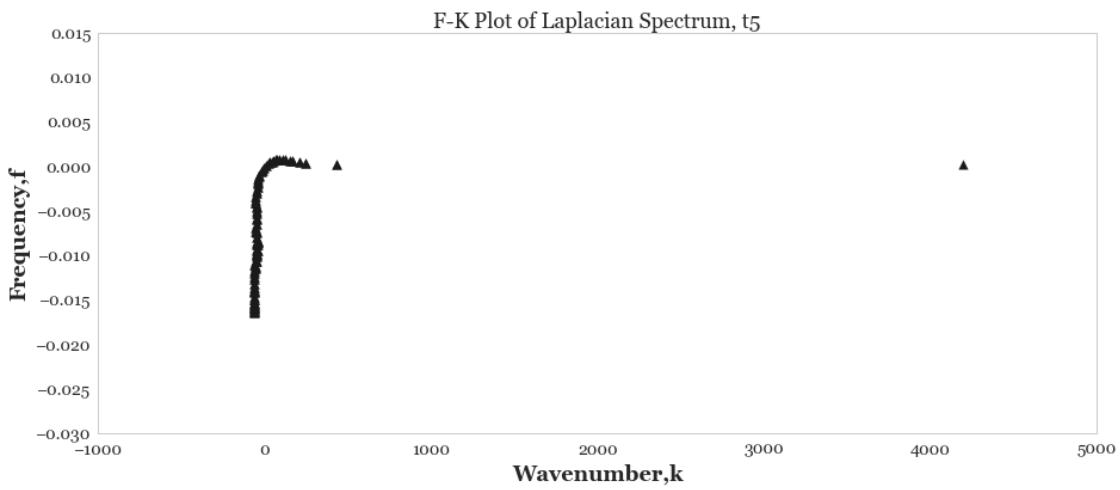
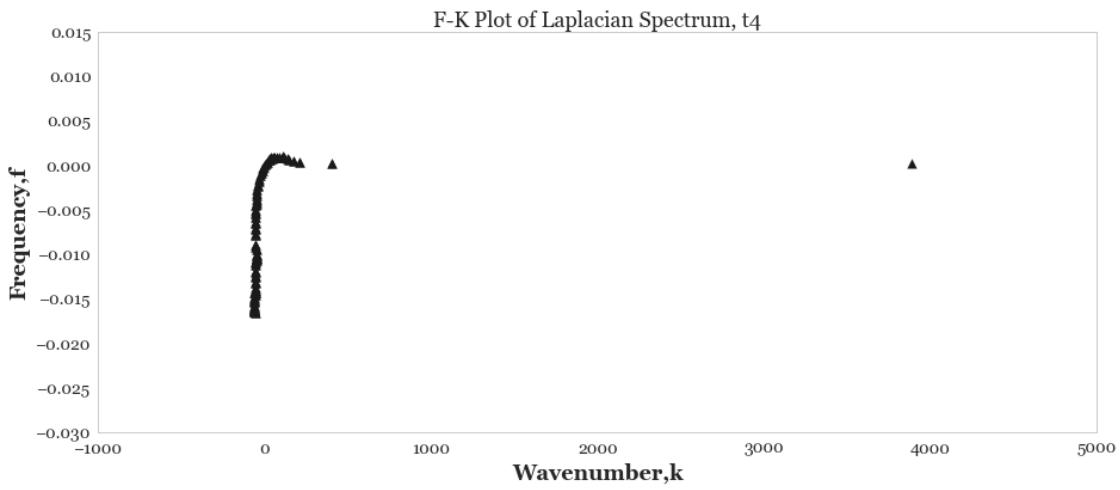
In [151]: freq01, k01 = fk_plot(lap_spec0,'Laplacian Spectrum, t0')
freq1, k1 = fk_plot(lap_spec1,'Laplacian Spectrum, t1')
freq2, k2 = fk_plot(lap_spec2,'Laplacian Spectrum, t2')
freq3, k3 = fk_plot(lap_spec3,'Laplacian Spectrum, t3')
freq4, k4 = fk_plot(lap_spec4,'Laplacian Spectrum, t4')
freq5, k5 = fk_plot(lap_spec5,'Laplacian Spectrum, t5')

C:\Users\arsha_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:533: ComplexWarning:
return array(a, dtype, copy=False, order=order, subok=True)

```

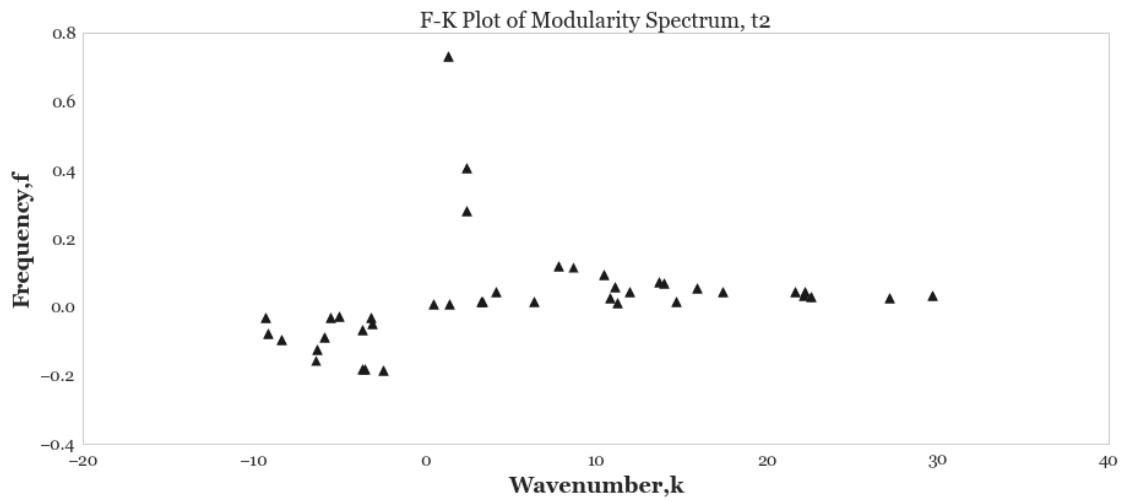
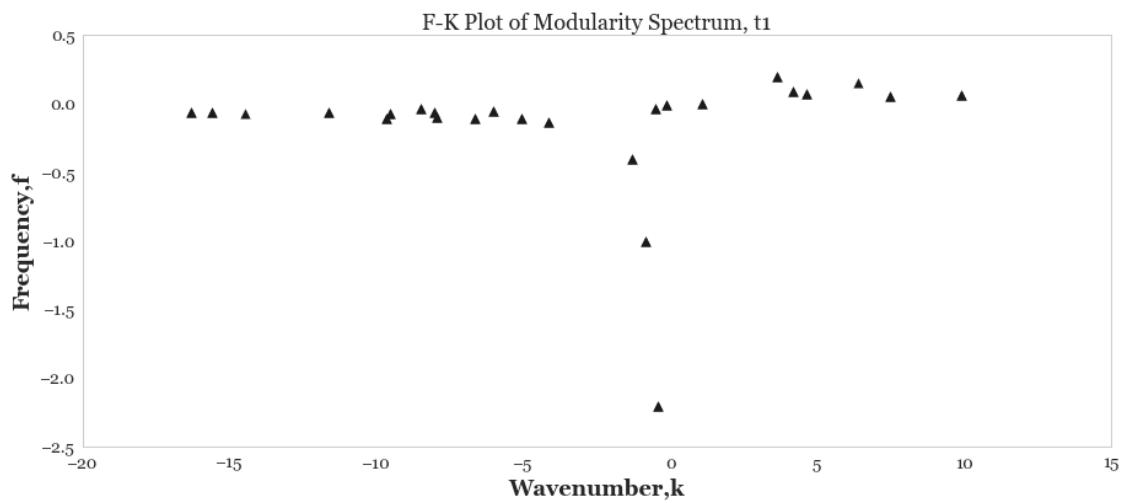
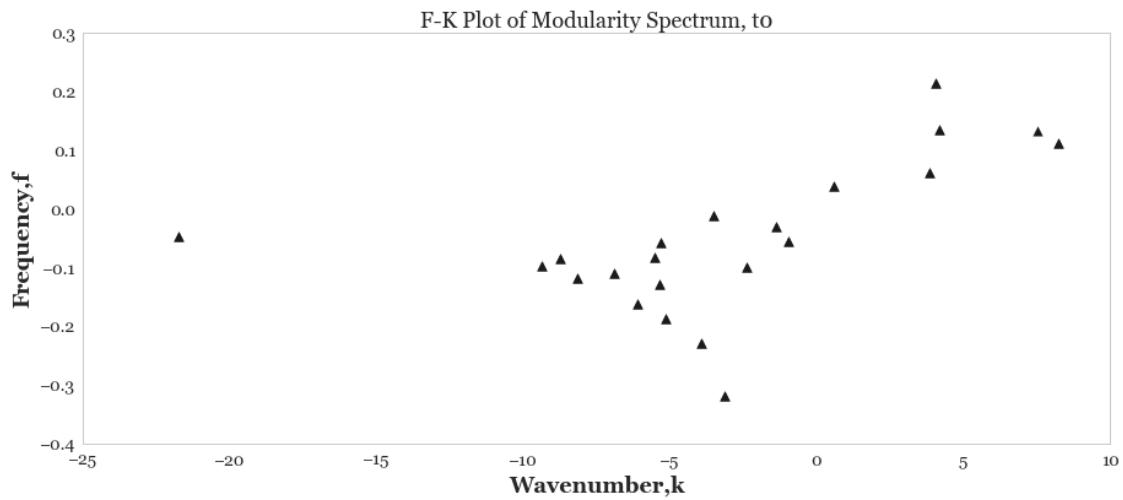


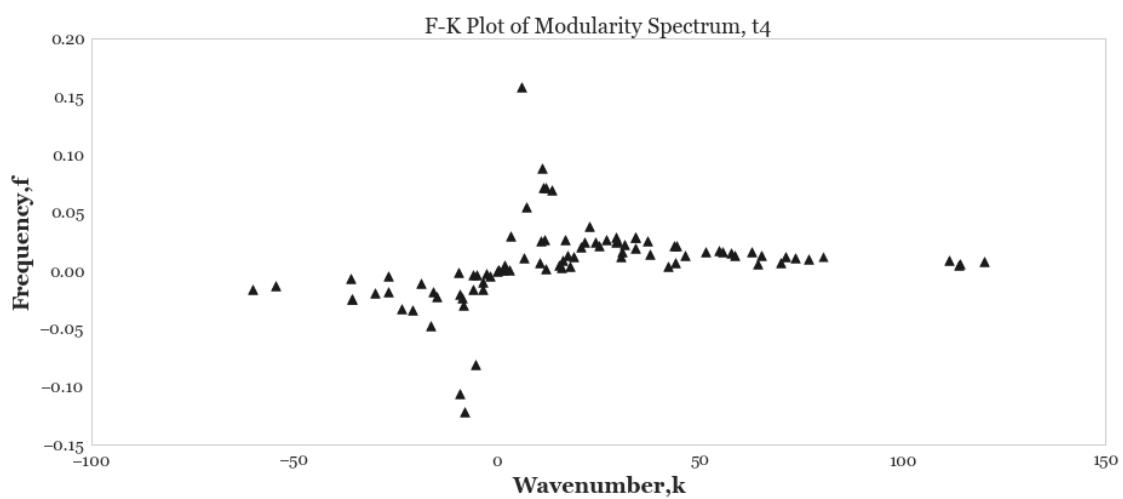
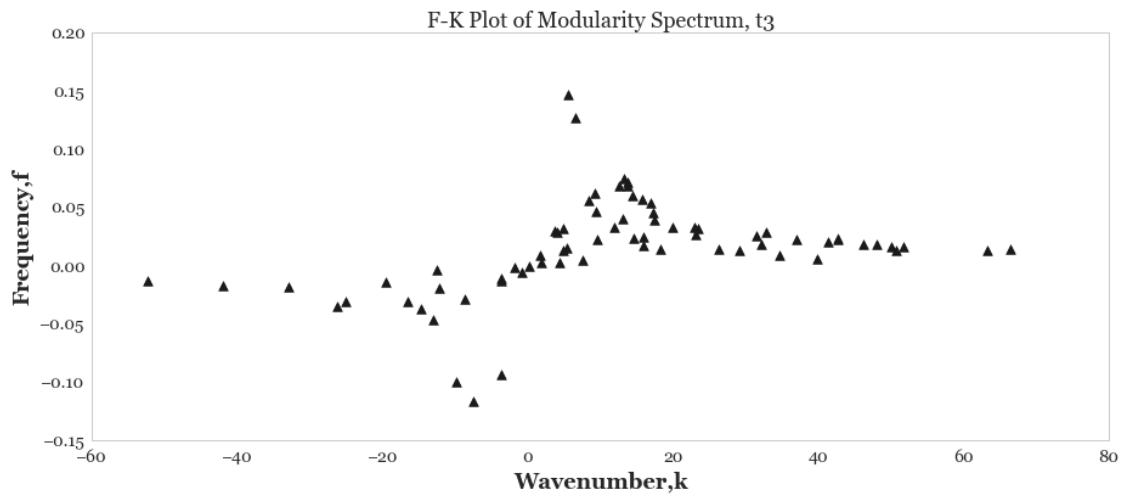


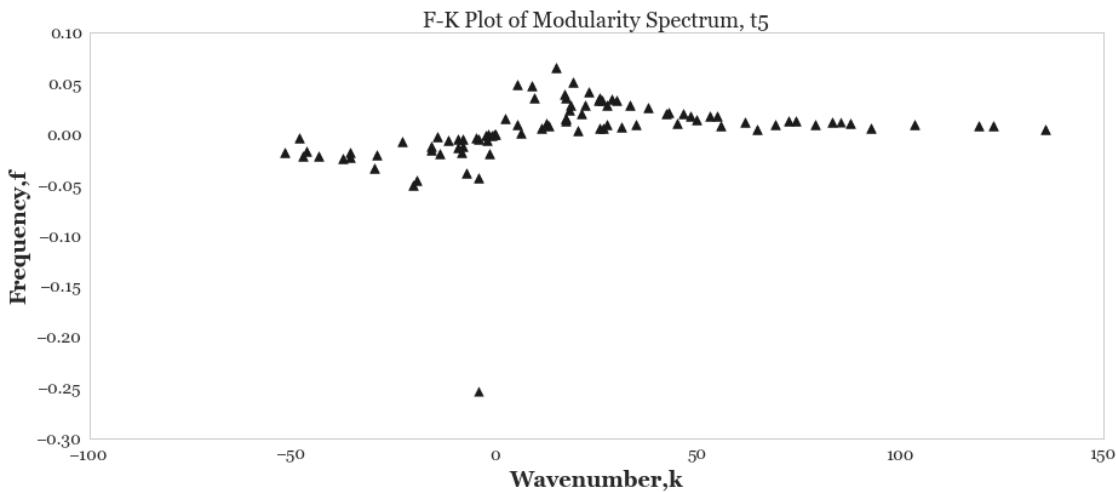


```
In [152]: freq02, k02 = fk_plot(mod_spec0, 'Modularity Spectrum, t0')
freq12, k02 = fk_plot(mod_spec1, 'Modularity Spectrum, t1')
freq22, k02 = fk_plot(mod_spec2, 'Modularity Spectrum, t2')
freq32, k02 = fk_plot(mod_spec3, 'Modularity Spectrum, t3')
freq42, k02 = fk_plot(mod_spec4, 'Modularity Spectrum, t4')
freq52, k02 = fk_plot(mod_spec5, 'Modularity Spectrum, t5')
```

```
C:\Users\arsha_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:533: ComplexWarning:
return array(a, dtype, copy=False, order=order, subok=True)
```

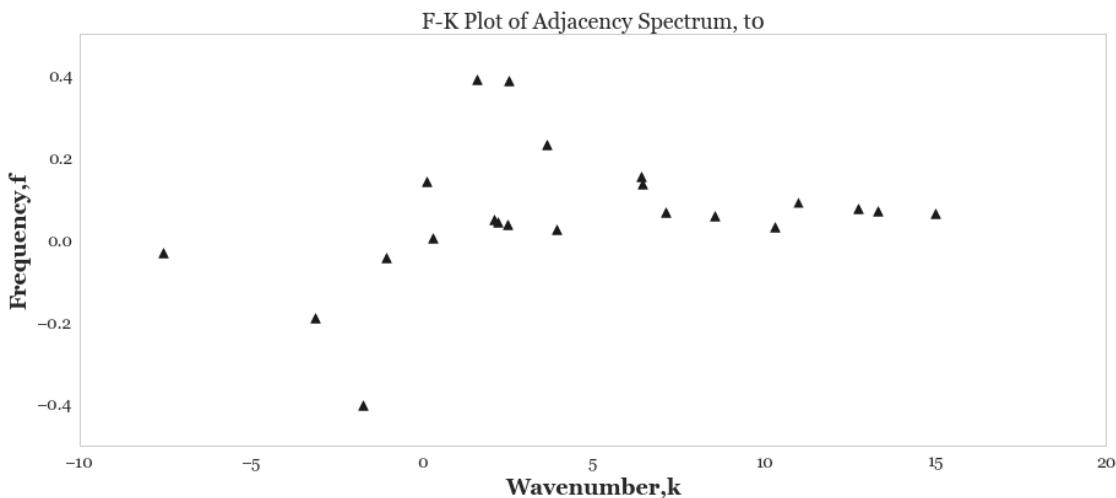




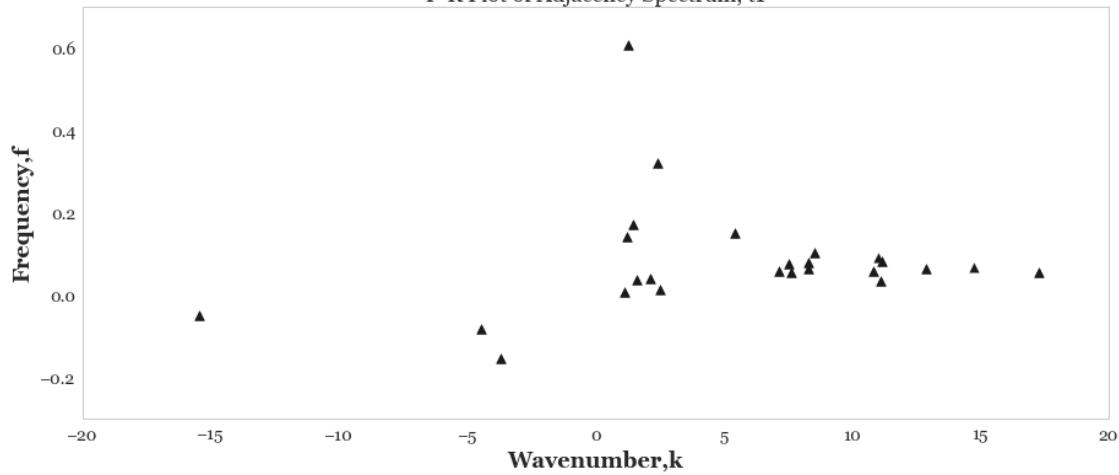


```
In [153]: freq03, k03 = fk_plot(adj_spec0, 'Adjacency Spectrum, t0')
freq13, k03 = fk_plot(adj_spec1, 'Adjacency Spectrum, t1')
freq23, k03 = fk_plot(adj_spec2, 'Adjacency Spectrum, t2')
freq33, k03 = fk_plot(adj_spec3, 'Adjacency Spectrum, t3')
freq43, k03 = fk_plot(adj_spec4, 'Adjacency Spectrum, t4')
freq53, k03 = fk_plot(adj_spec5, 'Adjacency Spectrum, t5')
```

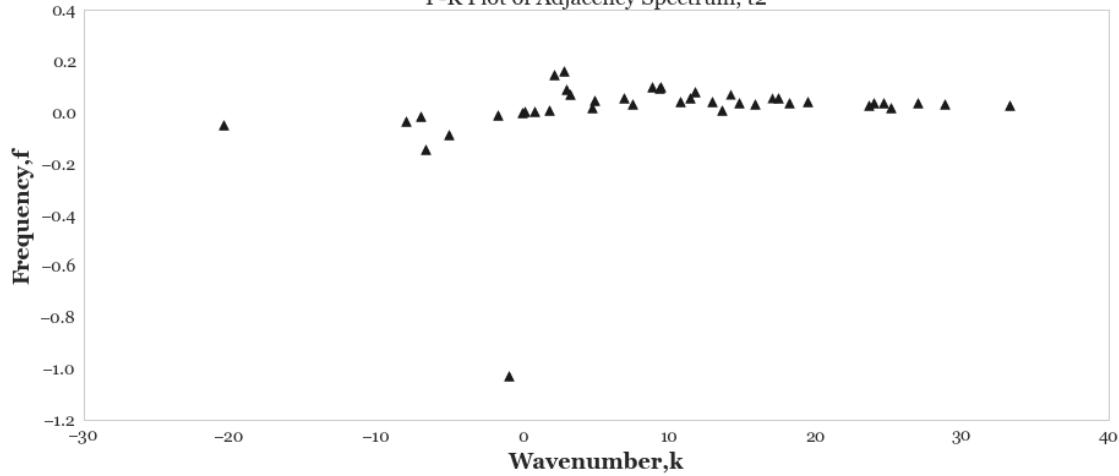
```
C:\Users\arsha_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:533: ComplexWarning:
return array(a, dtype, copy=False, order=order, subok=True)
```



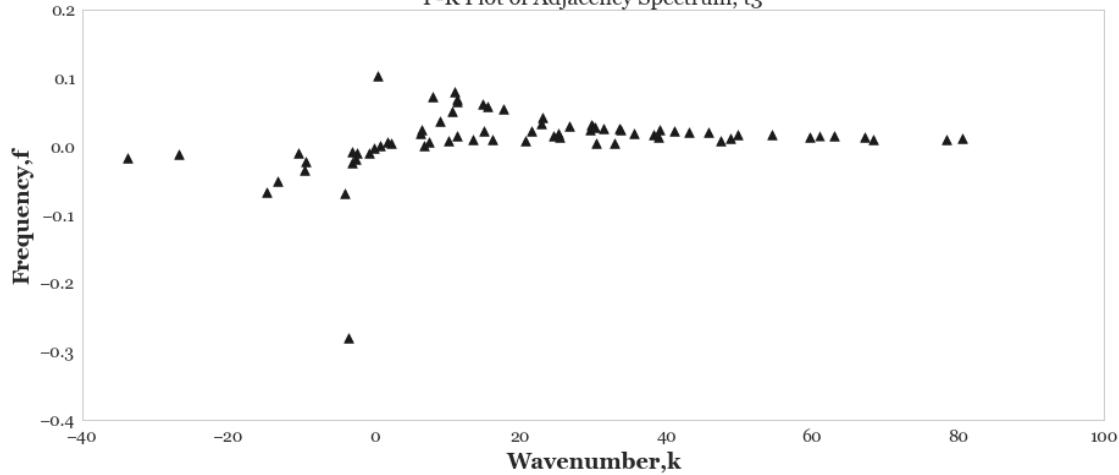
F-K Plot of Adjacency Spectrum, t1

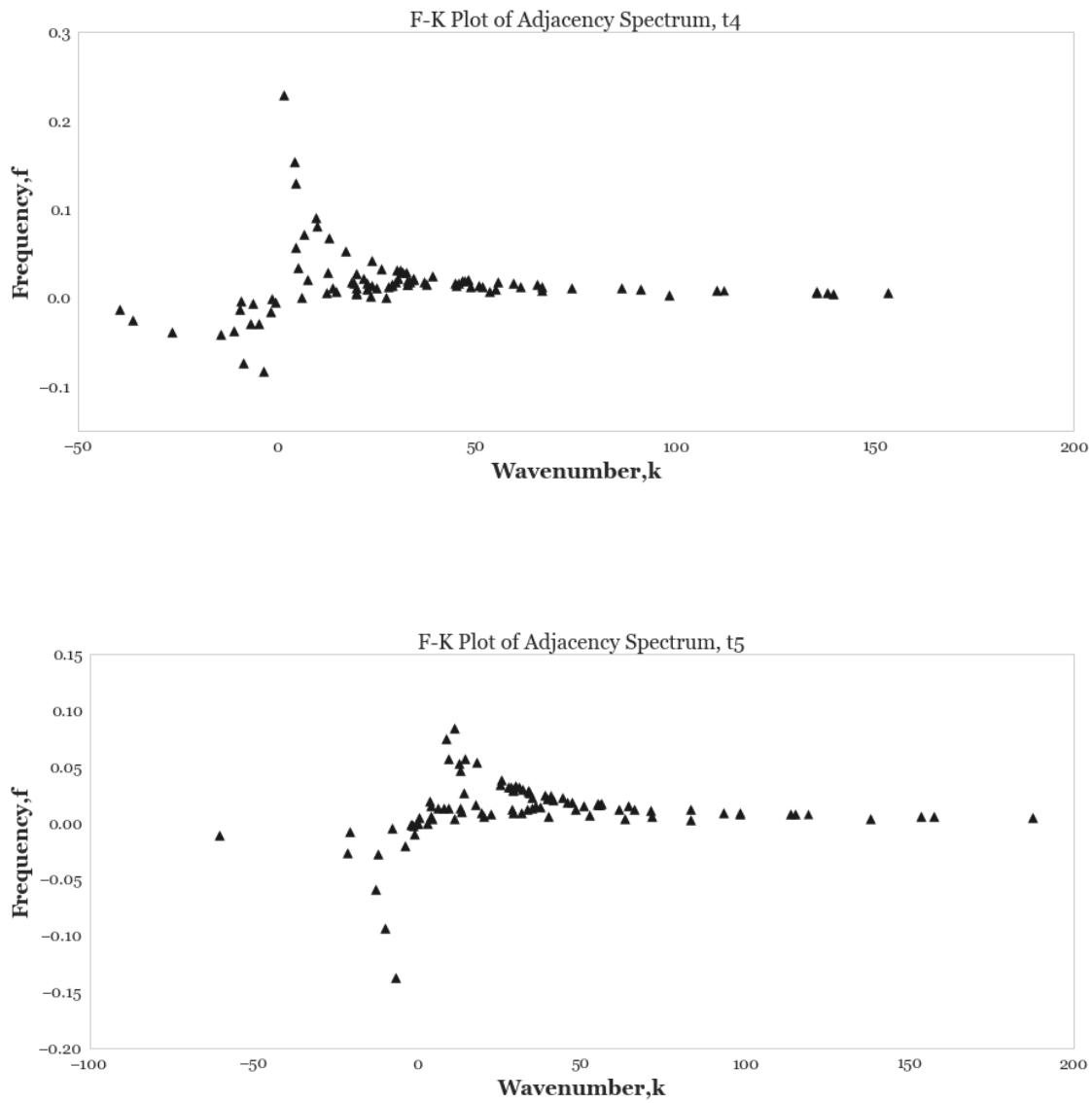


F-K Plot of Adjacency Spectrum, t2



F-K Plot of Adjacency Spectrum, t3





```
In [154]: freq_lap = pd.DataFrame([freq01,freq1,freq2,freq3,freq4,freq5]).T.apply(np.abs)
freq_adj = pd.DataFrame([freq03,freq13,freq23,freq33,freq43,freq53]).T.apply(np.abs)
freq_mod = pd.DataFrame([freq02,freq12,freq22,freq32,freq42,freq52]).T.apply(np.abs)

In [155]: plt.figure(figsize=(16, 6))

plt.subplot(131)
plt.plot(freq_lap)
plt.title('Plot of RMS of Laplacian Frequency Spectra, t0-t5', fontsize=14)
plt.xticks(fontsize=14)
```

```

plt.yticks(fontsize=14)
plt.xlabel("Time Step, t", fontsize=14)
plt.ylabel("RMS of Frequency", fontsize=14)

plt.subplot(132)
plt.plot(freq_adj)
plt.title('Plot of RMS of Adjacency Frequency Spectra, t0-t5', fontsize=14)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.legend(fontsize=16, loc=2)
plt.xlabel("Time Step, t", fontsize=14)
plt.ylabel("RMS of Frequency", fontsize=14)

plt.subplot(133)
plt.plot(freq_mod)
plt.title('Plot of RMS of Modularity Frequency Spectra, t0-t5', fontsize=14)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.legend(fontsize=16, loc=2)
plt.xlabel("Time Step, t", fontsize=14)
plt.ylabel("RMS of Frequency", fontsize=14)

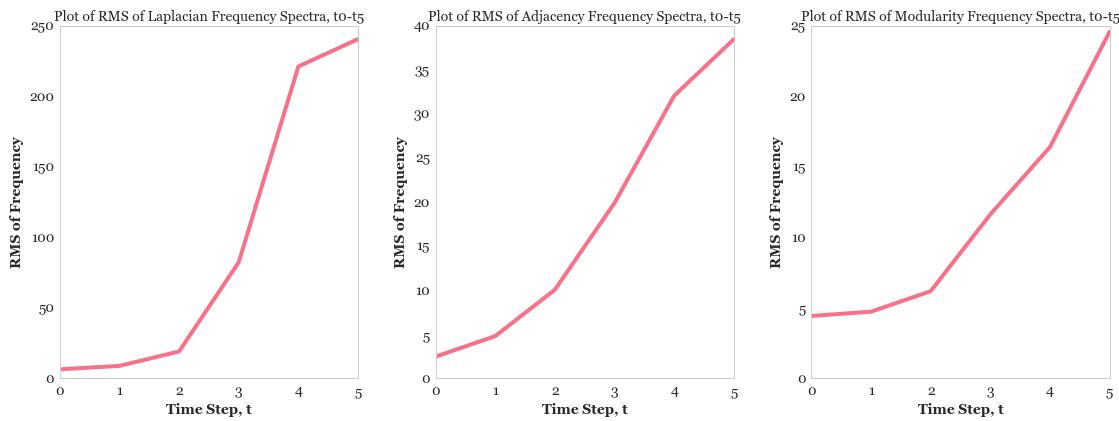
plt.tight_layout()

```

```

C:\Users\arsha_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:482: ComplexWarning:
  return array(a, dtype, copy=False, order=order)
C:\Users\arsha_000\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:519: UserWarning:
  warnings.warn("No labelled objects found. "

```



## 12 Radon Transform Plots

```
In [156]: def plot_radon(m, name):
    from skimage.transform import radon
    theta = np.linspace(0., 180., max(m.shape), endpoint=False)
    sinogram = radon(m, theta=theta, circle=True)

    fig, ax = plt.subplots(1,2)

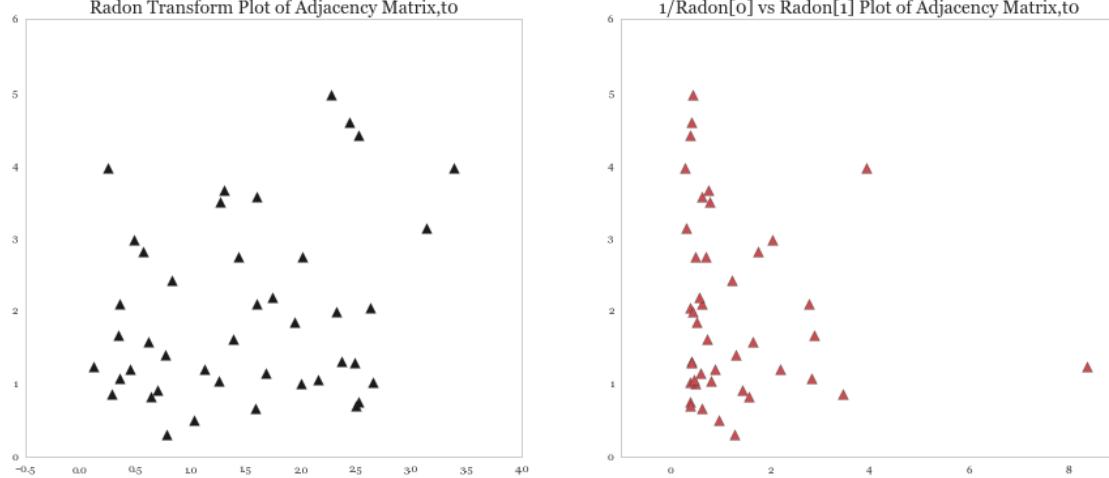
    ax[0].scatter(sinogram[0], sinogram[1], s=60, marker='^', c='k')
    ax[0].set_title("Radon Transform Plot of "+str(name), fontsize=14)

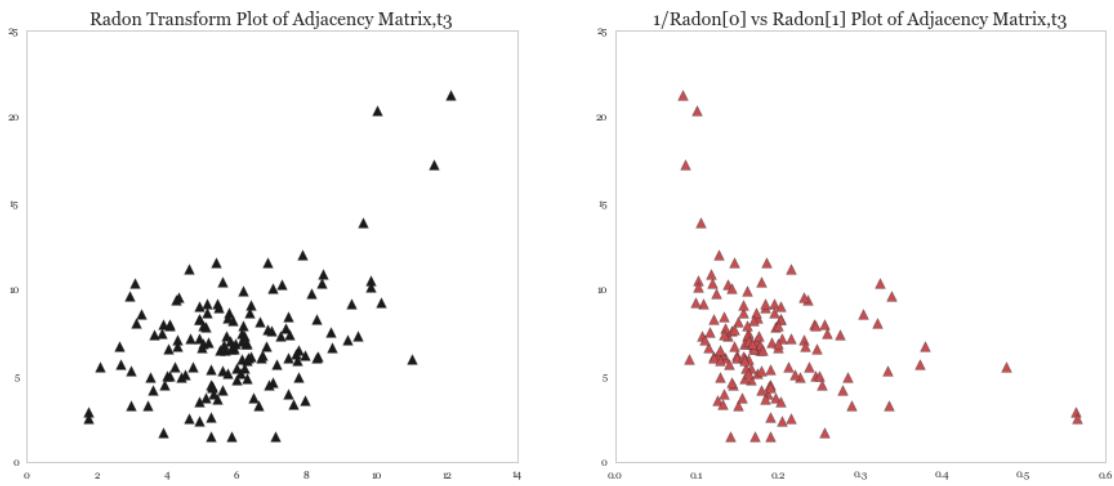
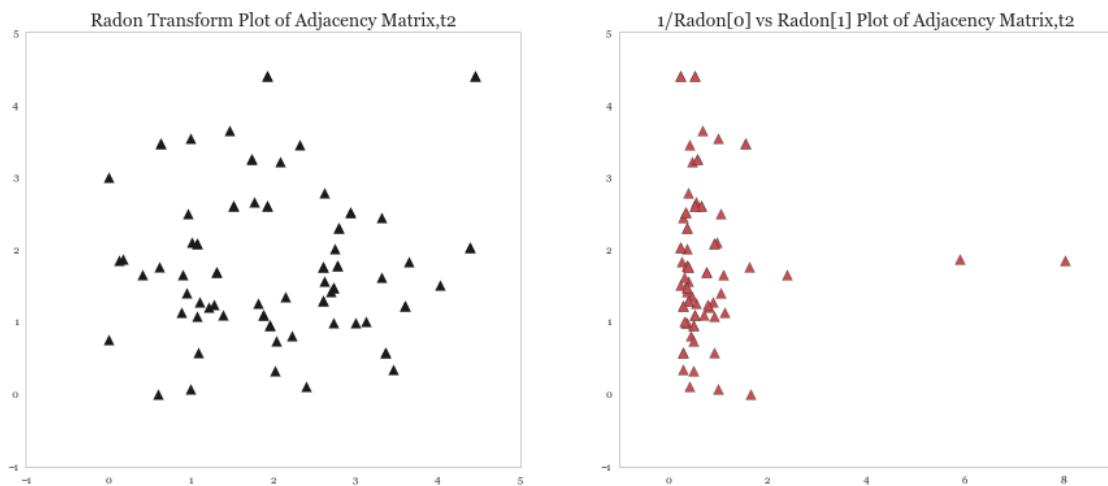
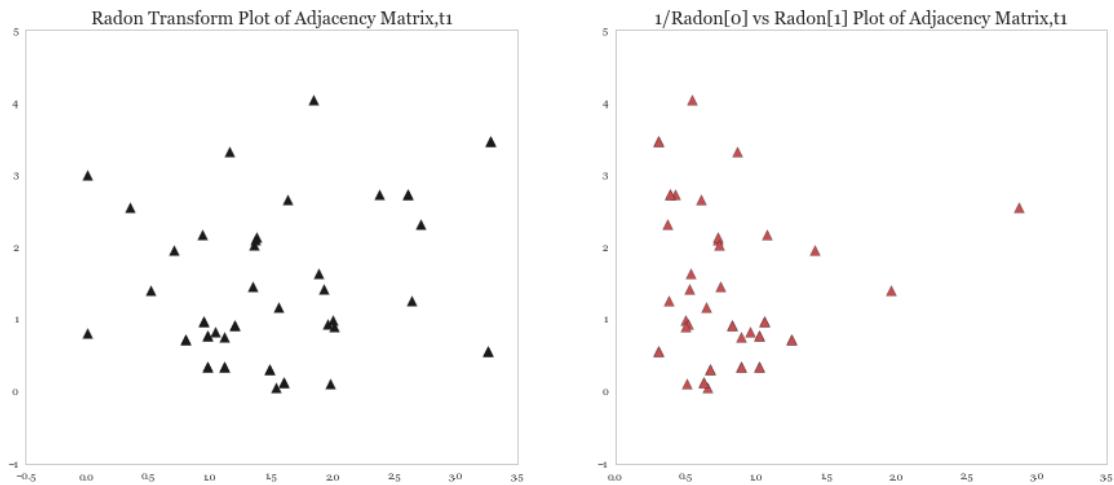
    ax[1].scatter(1/sinogram[0], sinogram[1], s=60, marker='^', c='r')
    ax[1].set_title("1/Radon[0] vs Radon[1] Plot of "+str(name), fontsize=14)

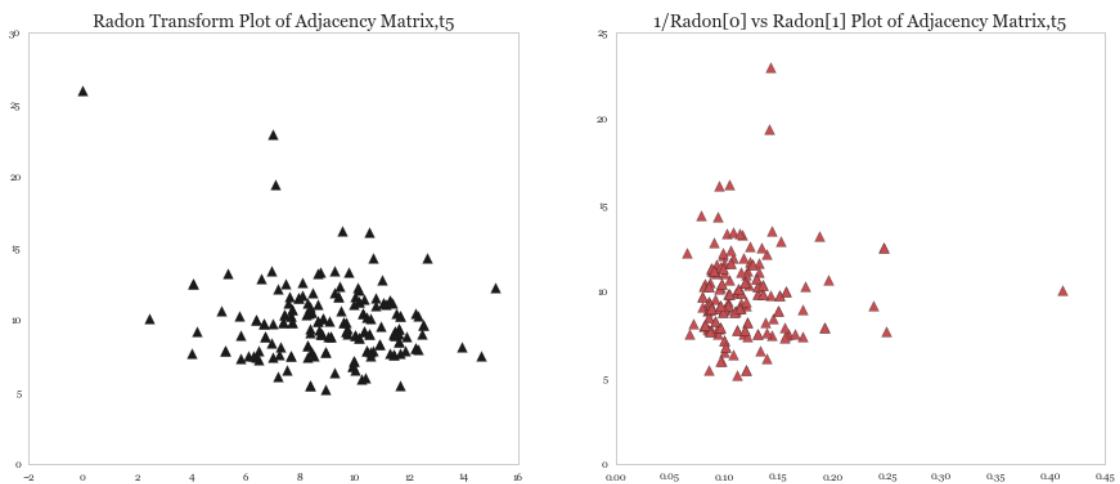
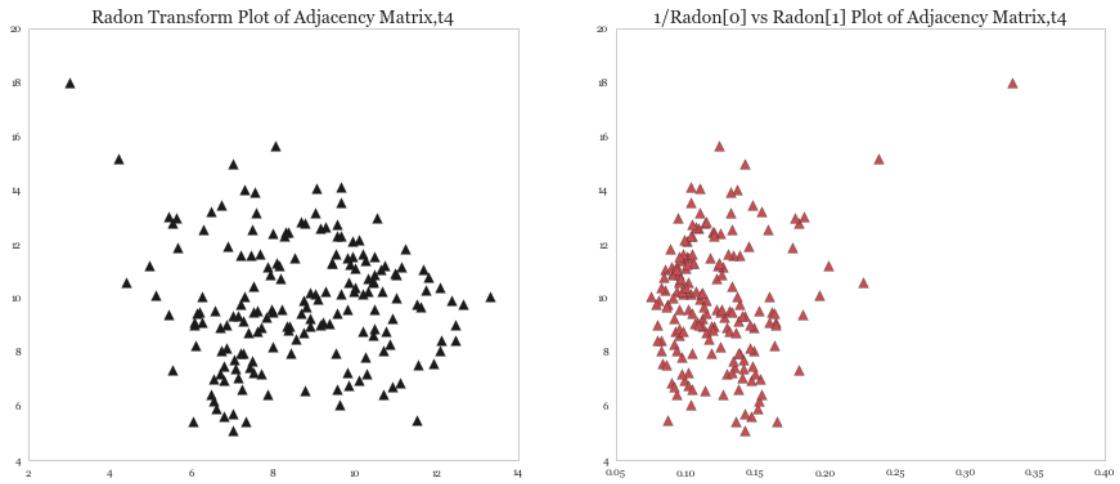
plt.show()

In [157]: plot_radon(adjM0, 'Adjacency Matrix,t0')
plot_radon(adjM1, 'Adjacency Matrix,t1')
plot_radon(adjM2, 'Adjacency Matrix,t2')
plot_radon(adjM3, 'Adjacency Matrix,t3')
plot_radon(adjM4, 'Adjacency Matrix,t4')
plot_radon(adjM5, 'Adjacency Matrix,t5')

C:\Users\arsha_000\Anaconda3\lib\site-packages\skimage\transform\radon_transform.py
warn('Radon transform: image must be zero outside the '
```

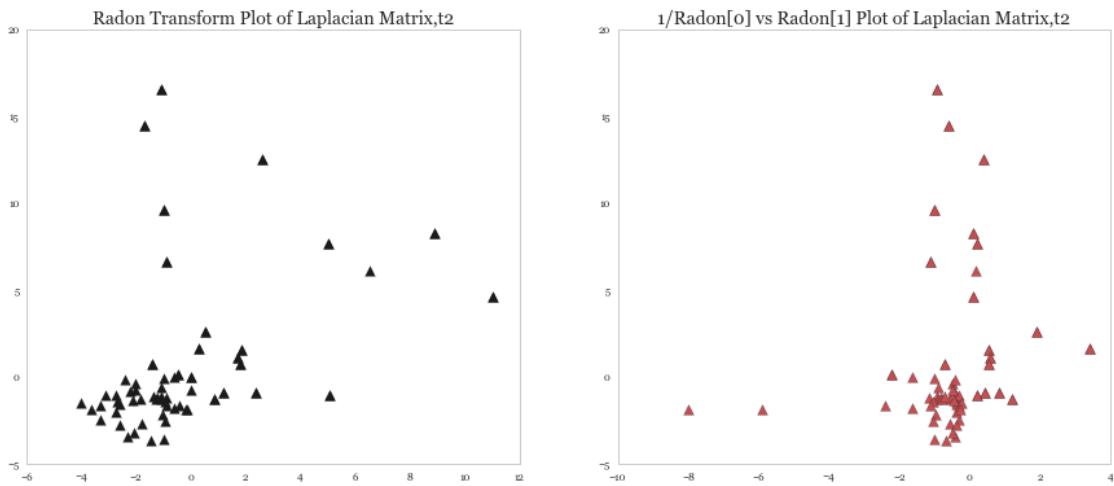
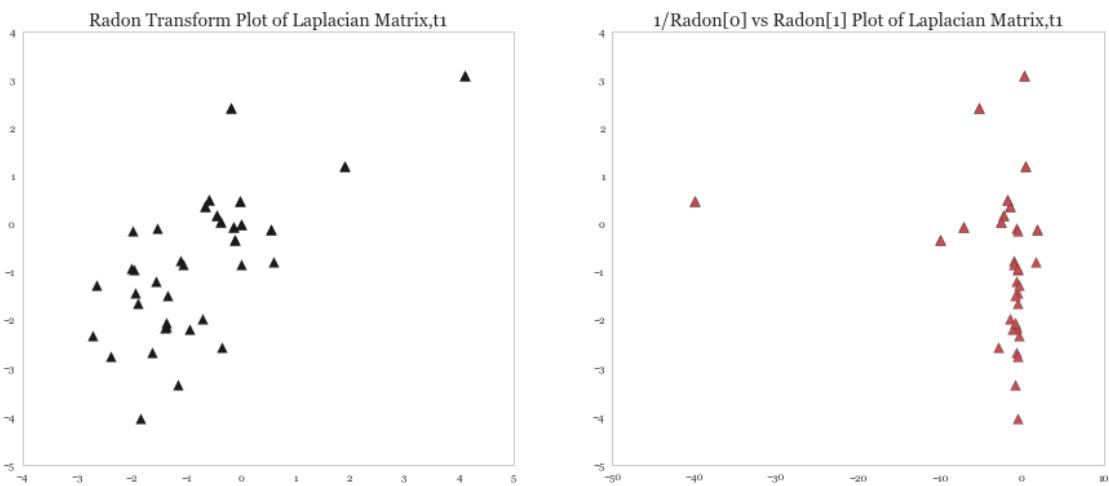
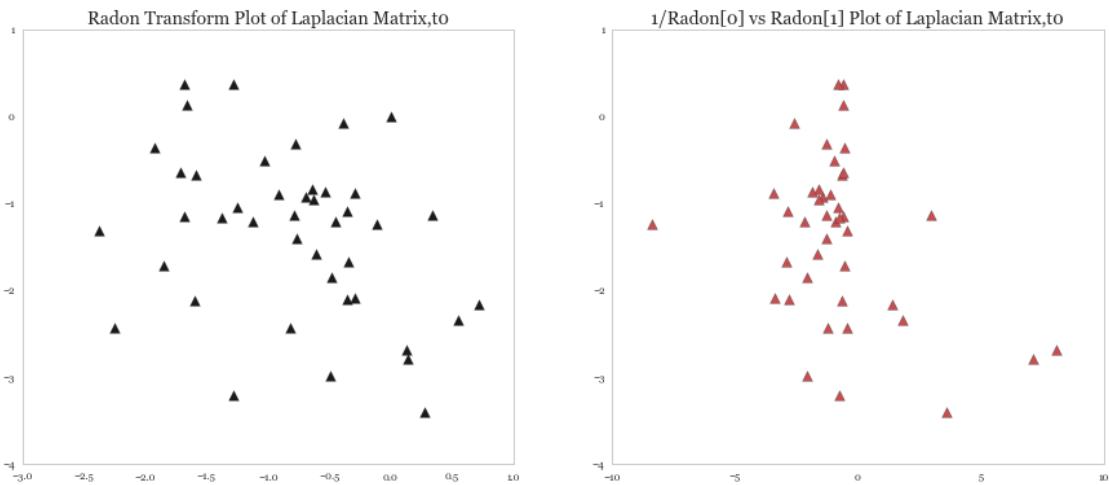


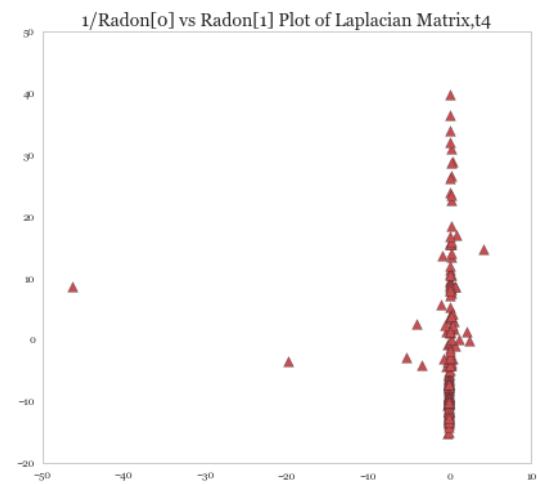
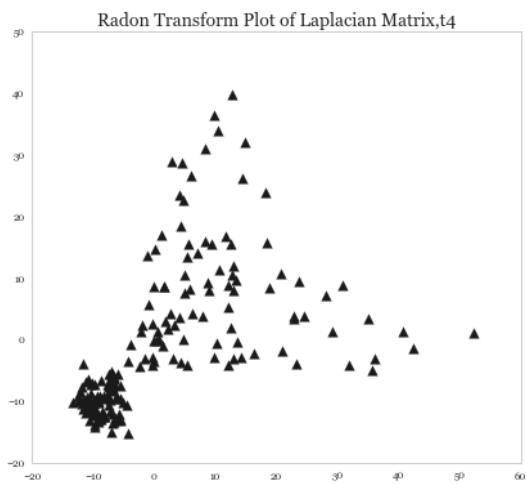
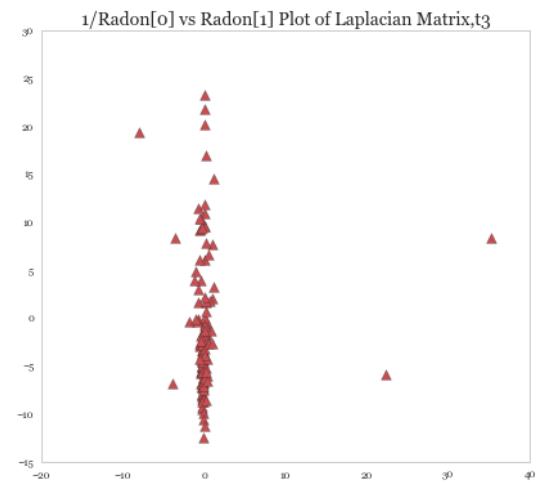
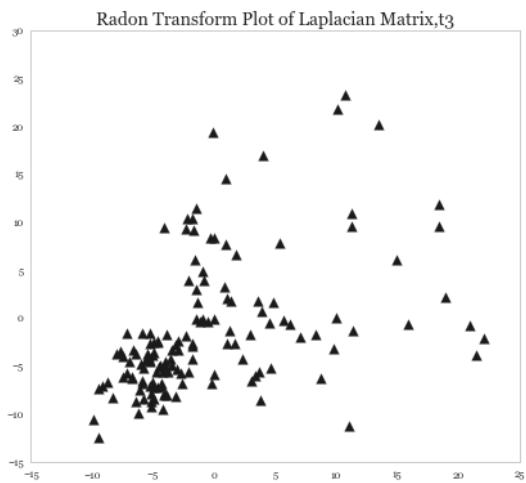


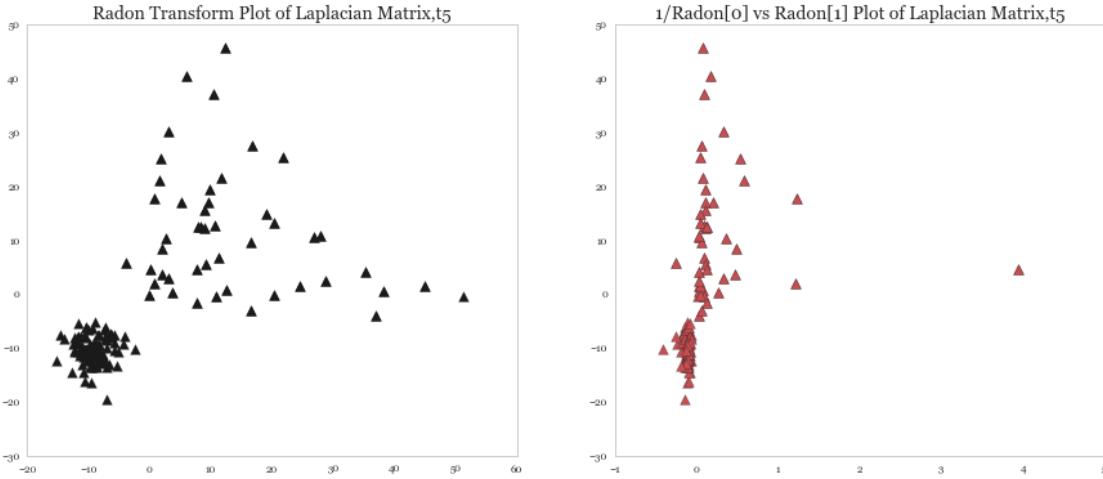


```
In [158]: plot_radon(lapM0, 'Laplacian Matrix,t0')
plot_radon(lapM1, 'Laplacian Matrix,t1')
plot_radon(lapM2, 'Laplacian Matrix,t2')
plot_radon(lapM3, 'Laplacian Matrix,t3')
plot_radon(lapM4, 'Laplacian Matrix,t4')
plot_radon(lapM5, 'Laplacian Matrix,t5')
```

C:\Users\arsha\_000\Anaconda3\lib\site-packages\skimage\transform\radon\_transform.py  
warn('Radon transform: image must be zero outside the ')







## 13 Instantaneous Frequency, $\omega$

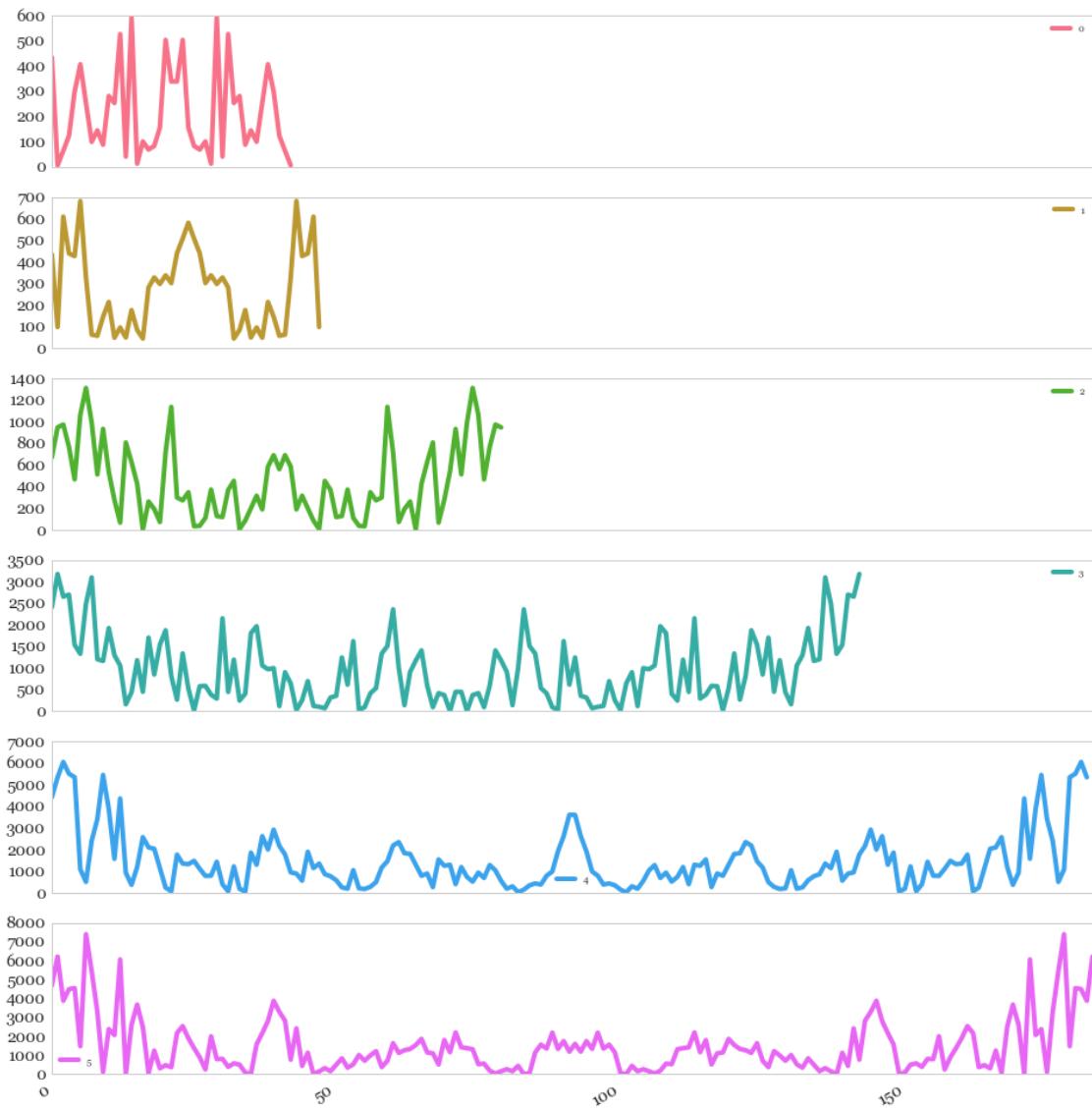
```
In [190]: ifreq_lap = pd.DataFrame([freq01,freq1,freq2,freq3,freq4,freq5]).T
ifreq_adj = pd.DataFrame([freq03,freq13,freq23,freq33,freq43,freq53]).T
ifreq_mod = pd.DataFrame([freq02,freq12,freq22,freq32,freq42,freq52]).T

In [191]: ifreq_adj= iphase_adj.applymap(lambda x: np.real(x)*2*np.pi)
ifreq_lap = iphase_lap.applymap(lambda x: np.real(x)*2*np.pi)
ifreq_mod = iphase_mod.applymap(lambda x: np.real(x)*2*np.pi)

In [211]: ifreq_adj.applymap(rms).plot(subplots=True, figsize=(16,18), fontsize=14)
plt.suptitle('RMS Instantaneous Frequency of Adjacency Matrix', fontsize=20)

Out[211]: <matplotlib.text.Text at 0x1addb49fa58>
```

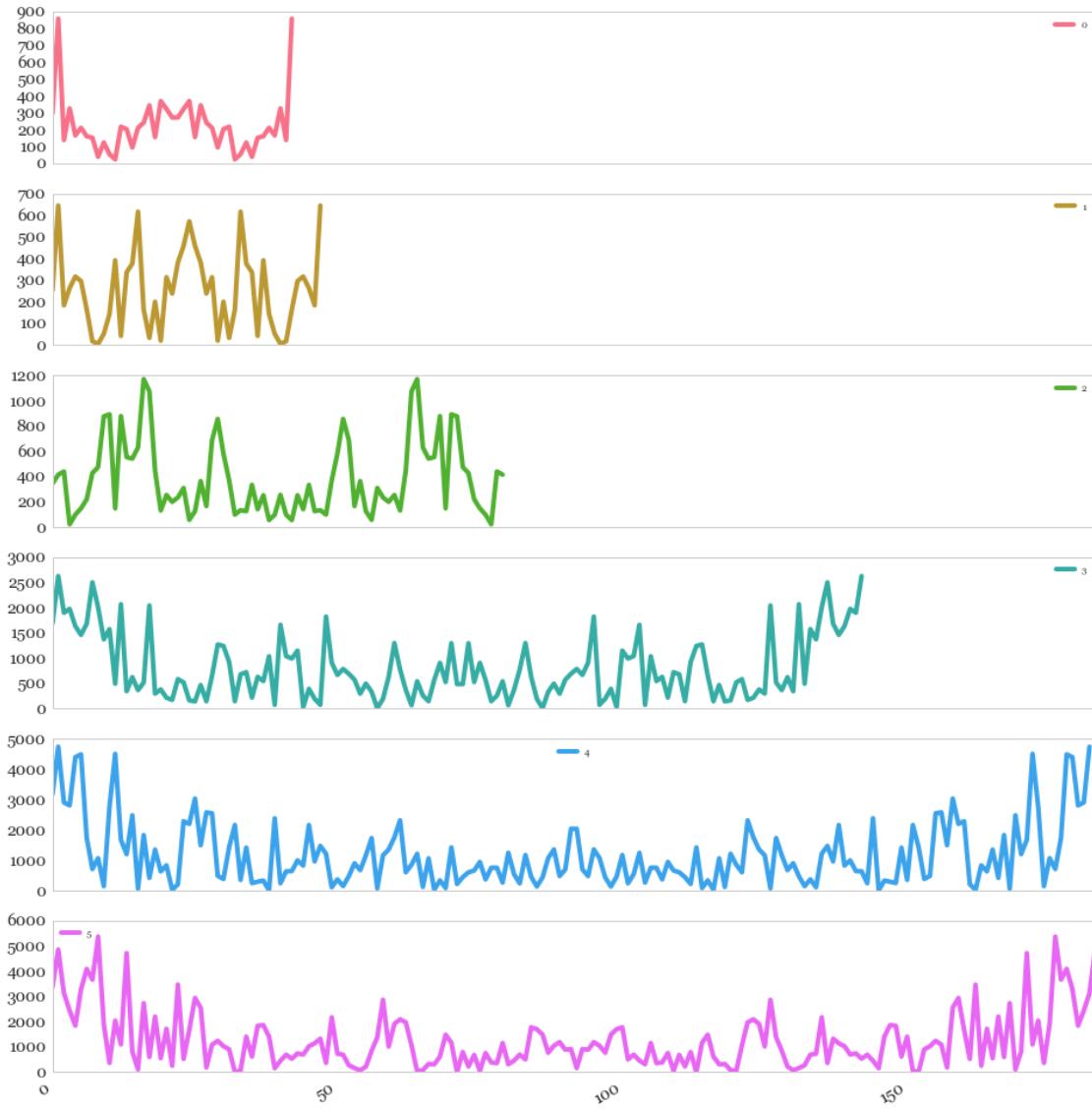
### RMS Instantaneous Frequency of Adjacency Matrix



```
In [208]: ifreq_mod.applymap(rms).plot(subplots=True, figsize=(16,18), fontsize=14)
plt.suptitle('RMS Instantaneous Frequency of Modularity Matrix', fontsize=16)
```

```
Out[208]: <matplotlib.text.Text at 0x1add9abf780>
```

### RMS Instantaneous Frequency of Modularity Matrix

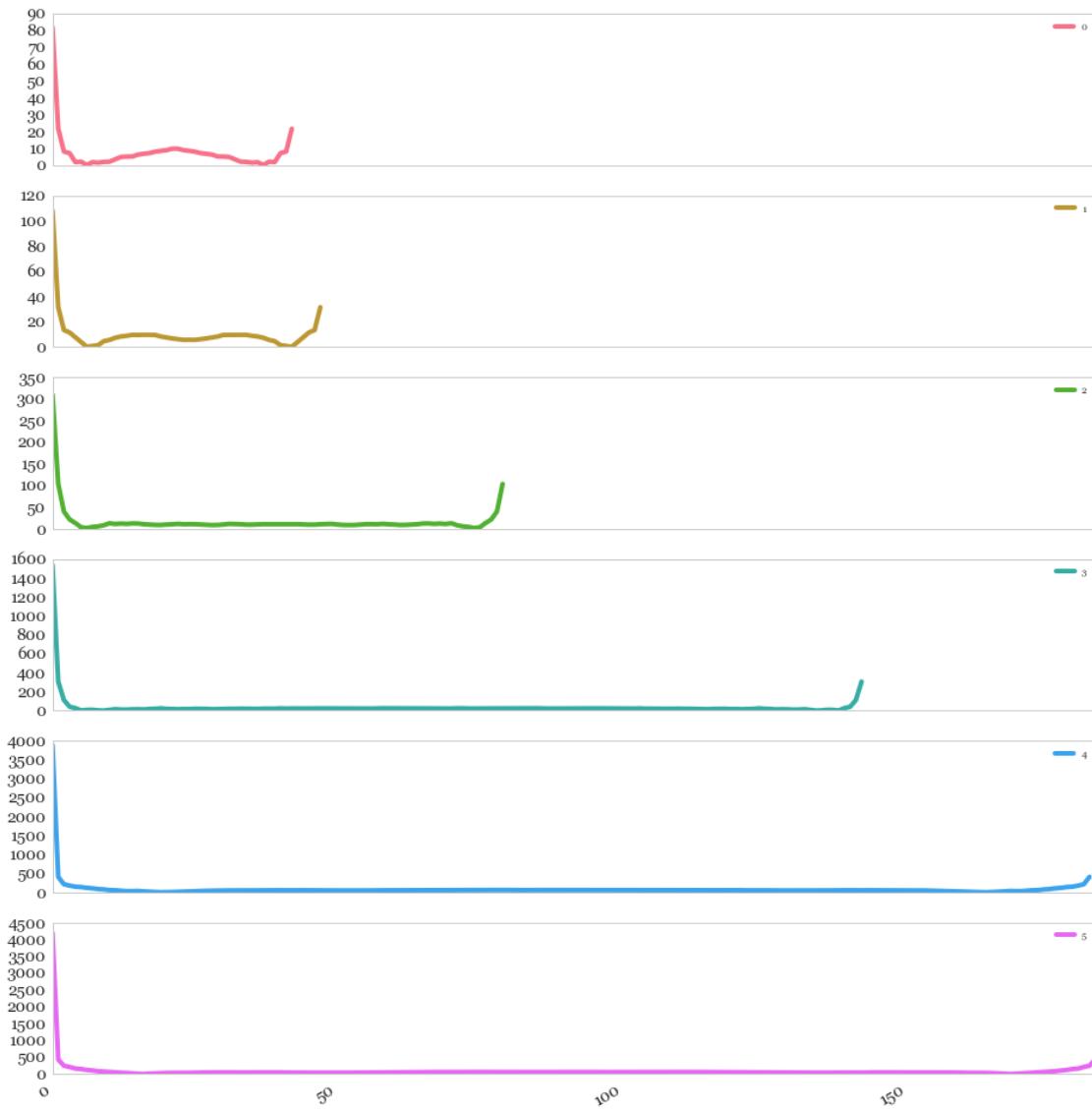


```
In [207]: ifreq_lap.applymap(rms).plot(subplots=True, figsize=(16,18), fontsize=14)
plt.suptitle('RMS Instantaneous Frequency of Laplacian Matrix', fontsize=20)
```

```
C:\Users\arsha_000\Anaconda3\lib\site-packages\numpy\ma\core.py:2720: ComplexWarning
  order=order, subok=True, ndmin=ndmin)
C:\Users\arsha_000\Anaconda3\lib\site-packages\numpy\core\numeric.py:482: ComplexWarning
  return array(a, dtype, copy=False, order=order)
```

```
Out[207]: <matplotlib.text.Text at 0x1add8cf1780>
```

### RMS Instantaneous Frequency of Laplacian Matrix



In [ ]: