

Nour El Orabi \ Lobna Aboudoma

```
In [1]: import numpy as np
import pandas as pd
from random import seed
from random import random
import matplotlib.pyplot as plt
import scipy.linalg as la
from sympy import *
import seaborn as sns
import numpy as np
import random
import sklearn
from sklearn import preprocessing
```

FACTORS AFFECTING CONVERGENCE RATE IN MARKOV CHAINS MONTE CARLO

HELPER FUNCTIONS

```
In [388... def print_statistics(list1, list2, name=[0,1]):
    df1 = pd.DataFrame(data = list1, columns = ['List1'])
    df2 = pd.DataFrame(data = list2, columns = ['List2'])
    d1 = df1.describe()
    d1 = d1.iloc[:,0]
    d2 = df2.describe()
    d2 = d2.iloc[:,0]
    df3 = pd.DataFrame(data = zip(d1,d2), columns = [name[0], name[1]])
    df3 = df3.set_index(pd.Index(['Count', 'Mean', 'Stdev', 'Minimum', '25%', '50%']))
    return df3
```

```
In [505... def print_statistics2(list_, names):
    a = [[]]
    #names = ['pr0', 'pr1', 'pr2', 'pr3']
    for i in range(len(names)):
        df = pd.DataFrame(data = list_[i])
        d = df.describe()
        d = np.array(d.iloc[:,0])
        d = d.tolist()
        an_array = np.array(list_[i])
        mean, standard_deviation = np.mean(an_array), np.std(an_array)
        distance_from_mean = abs(an_array - mean)
        max_deviations = 3
        not_outlier = distance_from_mean < max_deviations * standard_deviation
        no_outliers = an_array[not_outlier]
        d.append(len(list_[i])-len(no_outliers))
        a.append(d)
    df3 = pd.DataFrame(data = a)
    df3 = df3.transpose()
    df3 = df3.drop(columns = 0)
    df3.columns = names
    df3 = df3.set_index(pd.Index(['Count', 'Mean', 'Stdev', 'Minimum', '25%', '50%']))
    return df3
```

```
In [416... # Removes outliers that are the 3 standard deviations away from the mean, to
def remove_outliers(list):
    an_array = np.array(list)
    mean = np.mean(an_array)
    standard_deviation = np.std(an_array)
    distance_from_mean = abs(an_array - mean)
    max_deviations = 3
```

```

not_outlier = distance_from_mean < max_deviations * standard_deviation
no_outliers = an_array[not_outlier]
return no_outliers

```

```

In [10]: # Reducibility is being able to return to a state once the simulation starts
def check_reducibility(p):
    for i in range(len(p)):
        if(np.count_nonzero(p[i,:]==0)>1 or np.count_nonzero(p[:,i]==0)>1):
            return 1
        else:
            return 0

```

GENERATE MATRIX AND STATE

```

In [7]: # Generates a random matrix
def gen_matrix(n):
    # Start off with a matrix of zeros
    result=np.zeros((n,n))
    # generate random numbers from a uniform distribution and add them to the
    result = result + np.random.uniform(low=2, high=5, size=(n, n))
    # Normalize the matrix to have rows with sum = 1 for it to be a stochastic
    result = result / result.sum(axis=1, keepdims=1)
    return result

```

```

In [44]: def gen_matrix2(n):
    # Start off with a matrix of zeros
    result = np.zeros((n,n))
    # generate random numbers from a uniform distribution and add them to the
    result = result + np.random.uniform(low=0, high=0.25, size=(n, n))
    # round the values in the matrix to increase the probability of getting z
    result = np.around(result, decimals=1)
    # Normalize the matrix to have rows with sum = 1 for it to be a stochastic
    result = sklearn.preprocessing.normalize(result, norm="l1")
    return result

```

```

In [55]: def gen_matrix3(n):
    # create a variable that will store a random number deciding whether the
    aperiodic = np.random.randint(0,2)
    result = np.zeros((n,n))
    result = result + np.random.uniform(low=0, high=0.25, size=(n, n))
    result = np.around(result, decimals=1)
    if(aperiodic == 1):
        np.fill_diagonal(result, np.zeros(n))
    result = sklearn.preprocessing.normalize(result, norm="l1")
    return result

```

```

In [14]: # Generate random initial state
def gen_state(n):
    # takes the number of states and creates a list of zeros with the same si
    state = [[0]*n]
    state = np.array(state)
    # randomly choose a position in the list as the initial state
    state[:,np.random.randint(0,n)] = 1
    return state

```

GET CONVERGENCE

```

In [15]: def convergence(p, state,n):
    # User input:
    # p: NxN Matrix
    # state: Initial state
    # n: Number of states

```

```

stateHist=state
#dfStateHist=pd.DataFrame(state)
distr_his = np.array([[0] * n])
#create boolean variable reached that will stay false until the difference
# is 0.00001 and i will be a counter for the number of iterations it takes
reached = False
i = 0
while(reached == False):
    # set a limit for the number of iterations, anything greater than 200
    if(i>=2000):
        return i
    # increment the counter
    i = i+1
    # check the difference between the distributions in two iterations to
    y = state-np.dot(state,p)
    if(abs(y.all())<=0.00001):
        reached = True
        continue
    # in the case that it didn't converge, multiply the current distribution
    state=np.dot(state,p)
    # append the new distribution to the 2d array
    stateHist=np.append(stateHist,state,axis=0)
    dfDistrHist = pd.DataFrame(stateHist)
# return the counter for the number of iterations it takes to reach the state
return(i)

```

Factors Affecting Convergence Rate

1. Multiplicity of Eigenvalues

```

In [706... def check_multiplicity(mat):
    # Get the eigenvalues and eigenvectors from the matrix
    values, vectors= la.eig(mat.T)
    values = values.real
    # Get unique values and counts
    unique,indices,counts = np.unique(values,return_counts=True,return_index=True)
    #Check if eigenvalues are unique by checking if the number of the unique
    # This would mean that each column has a corresponding unique eigenvalue
    if(len(counts)==len(mat)):
        return 0
    #eigenvalues are not unique, multiplicity >1
    else:
        #print(counts)
        return 1

```

```

In [718... def check_multiplicity2(mat):
    # Get the eigenvalues and eigenvectors from the matrix
    values, vectors= la.eig(mat.T)
    values = values.real
    # Get unique values and counts
    unique,indices,counts = np.unique(values,return_counts=True,return_index=True)
    #Check if eigenvalues are unique by checking if the number of the unique
    # This would mean that each column has a corresponding unique eigenvalue
    #eigenvalues are not unique, multiplicity >1
    if(counts[0]>1):
        return 0
    else:
        return 1

```

```

In [763... def multiplicity(n):
    #create two empty lists to store values in
    unique = []
    not_unique = []
    for i in range(1000):
        # randomly generate a matrix and initial state
        p = gen_matrix2(n)
        state = gen_state(n)
        #Check multiplicity of the eigenvalues of the matrix p
        mult = check_multiplicity(p)
        #Depending on whether the eigenvalues are unique or not, we will add
        #list
        if(mult==0):
            unique.append(convergence(p,state,n))
        elif(mult==1):
            not_unique.append(convergence(p,state,n))
    # Plotting Distributions
    fig, (ax1, ax2) = plt.subplots(1,2, figsize = (24, 6))
    sns.histplot(data=remove_outliers(not_unique), ax=ax1,color='teal')
    sns.histplot( data=remove_outliers(unique), ax=ax2,color='teal')
    ax1.set_title('Non Unique Eigenvalues',fontsize=20)
    ax1.set_xlabel('Convergence Point',fontsize=15)
    ax1.set_ylabel('Count',fontsize=15)
    ax1.grid()
    ax2.set_title('Unique Eigenvalues',fontsize=20)
    ax2.set_xlabel('Convergence Point',fontsize=15)
    ax2.set_ylabel('Count',fontsize=15)
    ax2.grid()
    # Print statistics for the convergence points of both Unique and non-uniq
    return print_statistics2([not_unique], [ 'Non-Unique'])

```

```

In [760... multiplicity(3) #multiplicity function with state or matrix size of 6

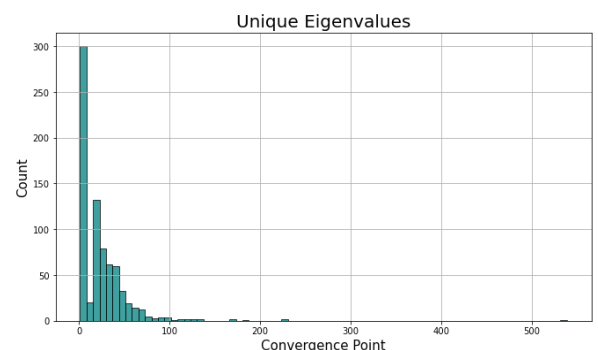
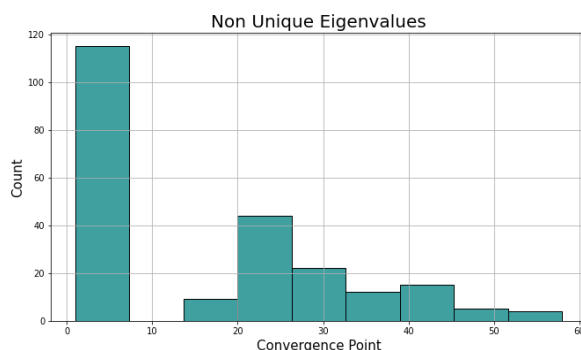
```

```

Out[760...

```

	Unique	Non-Unique
Count	773.000000	227.000000
Mean	50.371281	15.484581
Stdev	226.278791	16.215187
Minimum	1.000000	1.000000
25%	1.000000	1.000000
50%	20.000000	4.000000
75%	35.000000	27.000000
Max	2000.000000	66.000000
Outliers	11.000000	1.000000



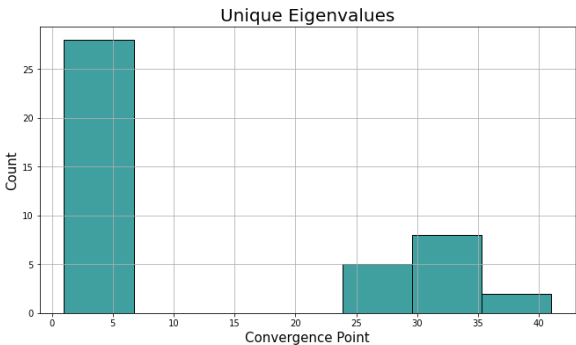
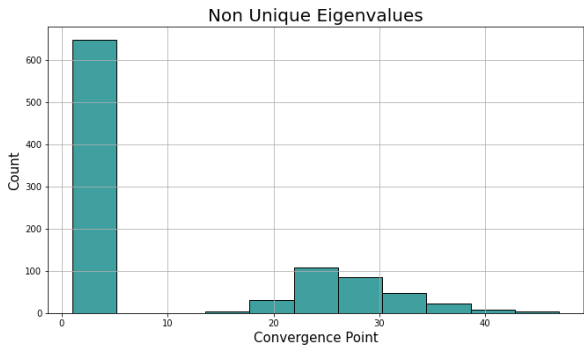
```

In [761... multiplicity(6) #multiplicity function with state or matrix size of 3

```

Out[761...

	Unique	Non-Unique
Count	43.000000	957.000000
Mean	11.395349	9.703239
Stdev	14.568622	13.011088
Minimum	1.000000	1.000000
25%	1.000000	1.000000
50%	1.000000	1.000000
75%	27.500000	24.000000
Max	41.000000	65.000000
Outliers	0.000000	2.000000

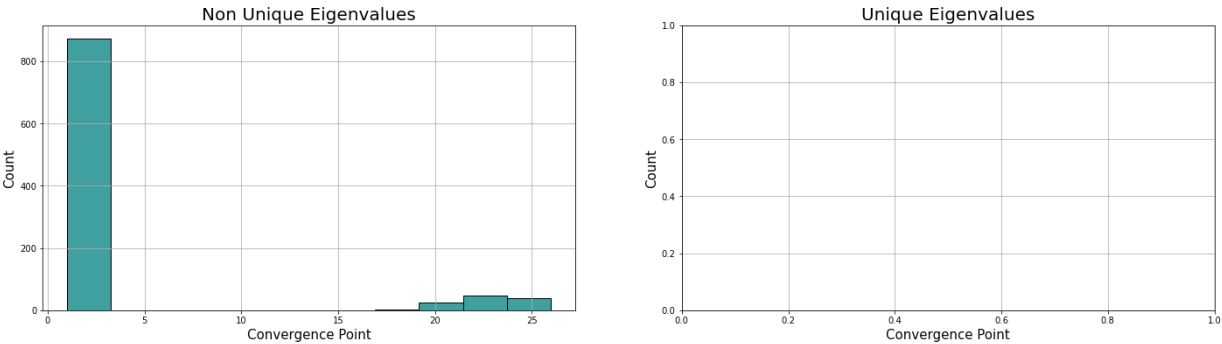


```
In [764... multiplicity(10) #multiplicity function with state or matrix size of 10

/Users/lobna/opt/anaconda3/lib/python3.8/site-packages/numpy/core/fromnumeric.py:3372: RuntimeWarning: Mean of empty slice.
  return _methods._mean(a, axis=axis, dtype=dtype,
/Users/lobna/opt/anaconda3/lib/python3.8/site-packages/numpy/core/_methods.py:170: RuntimeWarning: invalid value encountered in double_scalars
  ret = ret.dtype.type(ret / rcount)
/Users/lobna/opt/anaconda3/lib/python3.8/site-packages/numpy/core/_methods.py:233: RuntimeWarning: Degrees of freedom <= 0 for slice
  ret = _var(a, axis=axis, dtype=dtype, out=out, ddof=ddof,
/Users/lobna/opt/anaconda3/lib/python3.8/site-packages/numpy/core/_methods.py:194: RuntimeWarning: invalid value encountered in true_divide
  arrmean = um.true_divide(
/Users/lobna/opt/anaconda3/lib/python3.8/site-packages/numpy/core/_methods.py:226: RuntimeWarning: invalid value encountered in double_scalars
  ret = ret.dtype.type(ret / rcount)
```

Out[764...

	Non-Unique
Count	1000.000000
Mean	3.849000
Stdev	7.486404
Minimum	1.000000
25%	1.000000
50%	1.000000
75%	1.000000
Max	30.000000
Outliers	14.000000



2. Effect of Irreducibility on Convergence

```
In [592... def check_irreducible(mat):  
    mp = matrix_power(gen_matrix2(3), 4)  
    return np.count_nonzero(mp == 0)
```

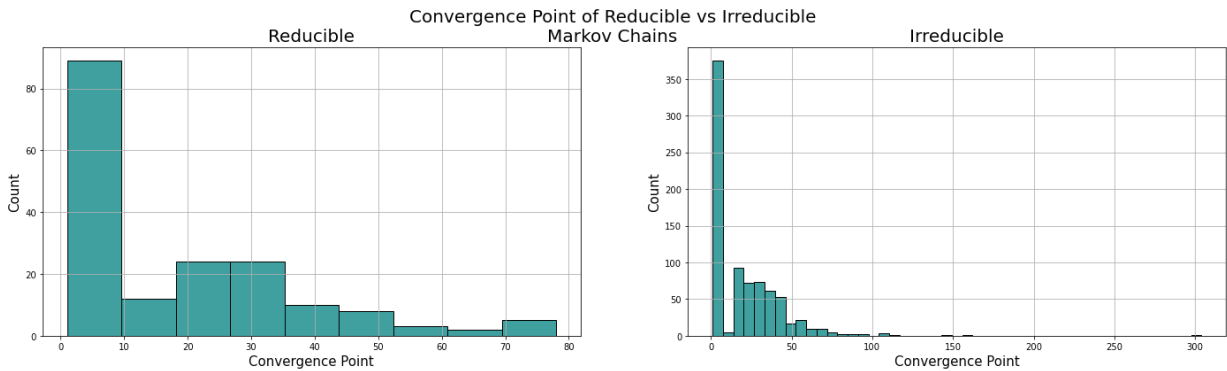
```
In [615... def irreducible(n):  
    #create two empty lists to store values in  
    reducible_ = []  
    irreducible_ = []  
    for i in range(1000):  
        # randomly generate a matrix and initial state  
        p = gen_matrix2(n)  
        state = gen_state(n)  
        red = check_irreducible(p)  
        if (red==0):  
            irreducible_.append(convergence(p,state,n))  
        elif (red!=0):  
            reducible_.append(convergence(p,state,n))  
    print_statistics(reducible_, irreducible_, ['Reducible', 'Irreducible'])  
    fig, (ax1, ax2) = plt.subplots(1,2, figsize = (24, 6))  
    sns.histplot(data=remove_outliers(reducible_), ax=ax1,color='teal')  
    sns.histplot( data=remove_outliers(irreducible_), ax=ax2,color='teal')  
    ax1.set_title('Reducible',fontsize=20)  
    ax1.set_xlabel('Convergence Point',fontsize=15)  
    ax1.set_ylabel('Count',fontsize=15)  
    ax1.grid()  
    ax2.set_title('Irreducible',fontsize=20)  
    ax2.set_xlabel('Convergence Point',fontsize=15)  
    ax2.set_ylabel('Count',fontsize=15)  
    ax2.grid()  
    fig.suptitle("Convergence Point of Reducible vs Irreducible \nMarkov Chain")  
    return print_statistics2([reducible_,irreducible_],['Reducible', 'Irreducible'])
```

```
In [624... irreducible(3) #irreducible function with state or matrix size of 3
```

Out[624...

	Reducible	Irreducible
Count	180.000000	820.000000
Mean	40.511111	49.290244
Stdev	195.170417	232.021664
Minimum	1.000000	1.000000
25%	1.000000	1.000000
50%	14.500000	16.000000
75%	29.000000	33.000000
Max	2000.000000	2000.000000

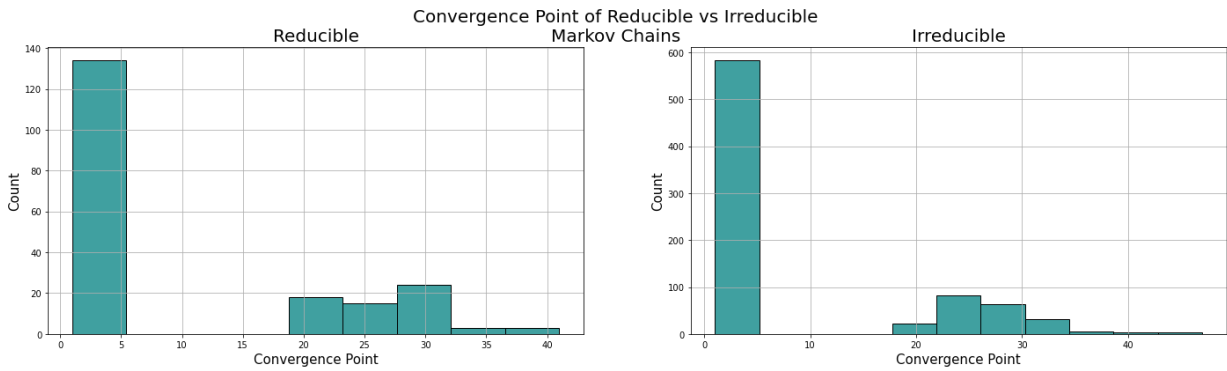
	Reducible	Irreducible
Outliers	3.000000	14.000000



```
In [632... irreducible(6) #irreducible function with state or matrix size of 6
```

Out[632...

	Reducible	Irreducible
Count	197.000000	803.000000
Mean	9.390863	8.494396
Stdev	12.495898	13.264089
Minimum	1.000000	1.000000
25%	1.000000	1.000000
50%	1.000000	1.000000
75%	23.000000	21.000000
Max	41.000000	135.000000
Outliers	0.000000	5.000000

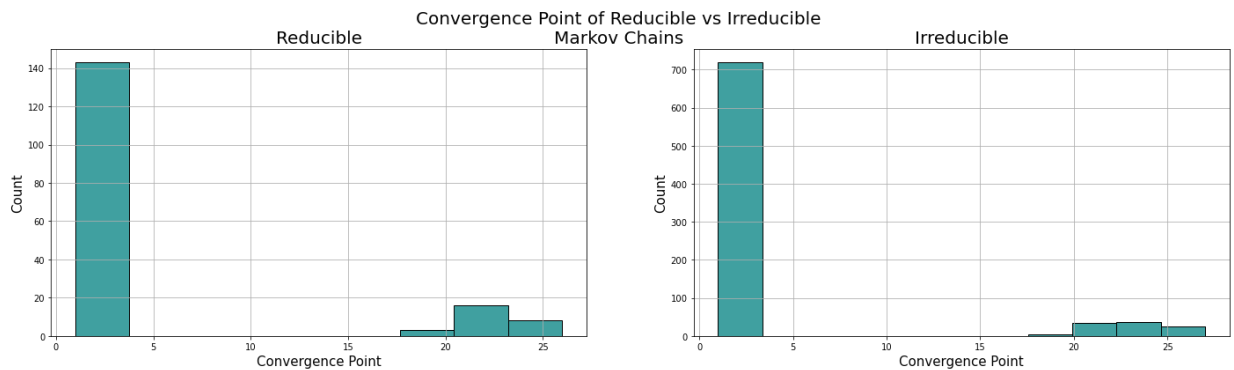


```
In [633... irreducible(10) #irreducible function with state or matrix size of 10
```

Out[633...

	Reducible	Irreducible
Count	170.000000	830.000000
Mean	4.464706	4.045783
Stdev	8.025215	7.835789
Minimum	1.000000	1.000000
25%	1.000000	1.000000
50%	1.000000	1.000000
75%	1.000000	1.000000

	Reducible	Irreducible
Max	26.000000	40.000000
Outliers	0.000000	10.000000



3. Periodic Versus Aperiodic

In [364...

```
def get_periodicity(mat):
    # Create an empty list to store the period of each state in
    periods = []
    # Loop over the number of states
    for i in range(len(mat)):
        period = 0
        # If there exists a path from the state returning to the same state,
        if(mat[i,i]!=0):
            periods.append(1)
            continue
        # Check if the sum of the column is 0 then there exists no path return
        # hence period is undefined
        elif((mat[:,i].sum(axis=0)==0)):
            periods.append(0)
            continue
        # Check the connected states if they return back to the state in inte
        else:
            # Get the indices of the non-zero values in the row of the state
            y = np.array(np.nonzero(np.array(mat[i,:]))))
            y= y[0,:]
            # Loop over the connected states and check their corresponding ro
            for x in y:
                # If the neighboring state is connected to i, then the period
                if(mat[x,i]!=0):
                    periods.append(2)
                    break
                continue
            # If the period isn't undefined, 1 , or 2, then the period is 3
            else:
                periods.append(3)
                continue
    # Return the number of transient states, that have undefined periods
    return np.count_nonzero(np.array(periods) == 1)
```

In [585...

```
def periodic():
    #create two empty lists to store values in
    pr0 = []
    pr1 = []
    pr2 = []
    pr3 = []
    for i in range(1000):
        # randomly generate a matrix and initial state
        p = gen_matrix2(3)
```



```

state = gen_state(3)
pr = get_periodicity(p)
# perds = [0,1,2,3]
# indices = [i for i, s in enumerate(perds) if pr in s]
if(pr==0):
    pr0.append(convergence(p,state,3))
elif(pr==1):
    pr1.append(convergence(p,state,3))
elif(pr==2):
    pr2.append(convergence(p,state,3))
elif(pr==3):
    pr3.append(convergence(p,state,3))

fig, ((ax1, ax2), (ax3,ax4)) = plt.subplots(2, 2, figsize = (15, 10))
sns.histplot(data=remove_outliers(pr0), ax=ax1,color='teal')
sns.histplot(data=remove_outliers(pr1), ax=ax2,color='teal')
sns.histplot(data = remove_outliers(pr2), ax=ax3, color='teal')
sns.histplot(data = remove_outliers(pr3), ax=ax4, color='teal')
ax1.set_title('0 Aperiodic States',fontsize=20)
ax1.set_xlabel('Convergence Point',fontsize=15)
ax1.set_ylabel('Count',fontsize=15)
ax1.grid()
ax2.set_title('1 Aperiodic State',fontsize=20)
ax2.set_xlabel('Convergence Point',fontsize=15)
ax2.set_ylabel('Count',fontsize=15)
ax2.grid()
ax3.set_title('2 Aperiodic States',fontsize=20)
ax3.set_xlabel('Convergence Point',fontsize=15)
ax3.set_ylabel('Count',fontsize=15)
ax4.set_title('Aperiodic Chain',fontsize=20)
ax4.set_xlabel('Convergence Point',fontsize=15)
ax4.set_ylabel('Count',fontsize=15)
fig.suptitle("Point of Convergence of Markov Chains with \n Varying Number of States",fontsize=15)
fig.tight_layout()
ax4.grid()
ax3.grid()
return print_statistics2([pr0, pr1, pr2, pr3], ['0 States','1 State','2 States','Aperiodic Chain'])

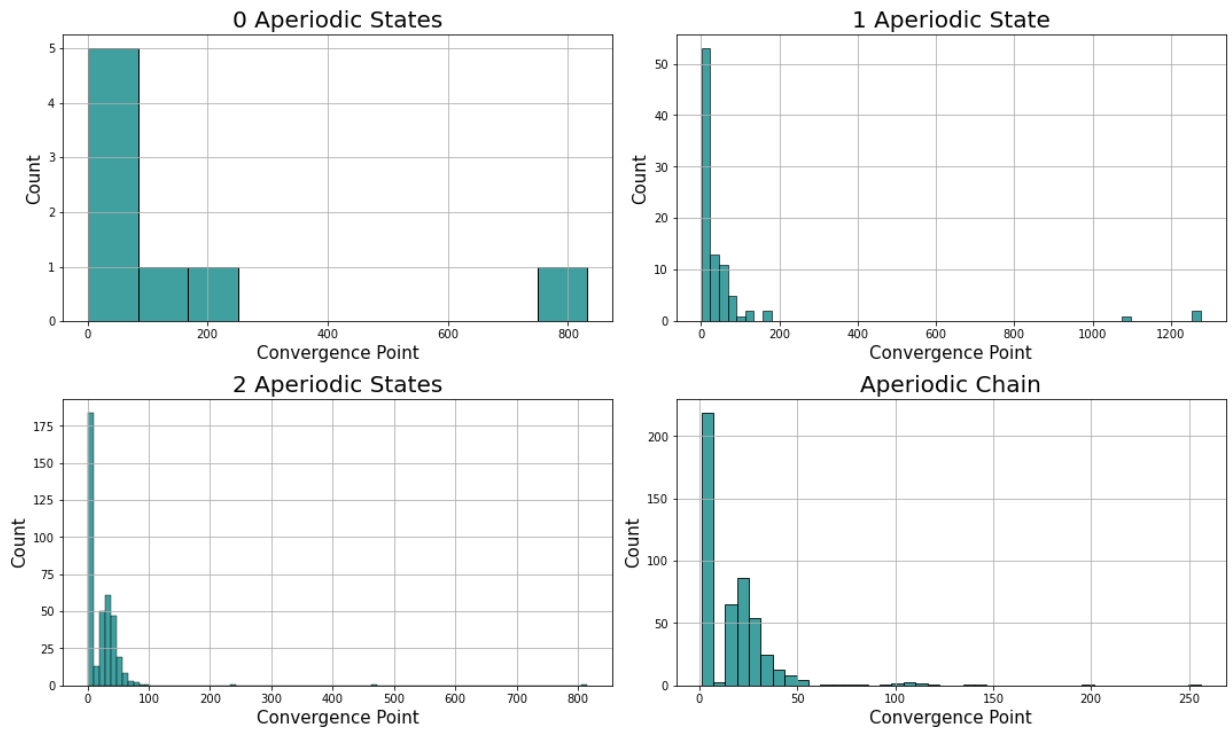
```

In [637... periodic() #periodic function

Out[637...

	0 States	1 State	2 States	Aperiodic
Count	8.000000	95.000000	401.000000	496.000000
Mean	159.125000	156.842105	64.950125	22.235887
Stdev	278.026945	446.211411	281.017717	93.180691
Minimum	1.000000	1.000000	1.000000	1.000000
25%	28.250000	1.000000	1.000000	1.000000
50%	63.500000	2.000000	22.000000	16.000000
75%	113.500000	56.500000	37.000000	25.000000
Max	832.000000	2000.000000	2000.000000	2000.000000
Outliers	0.000000	5.000000	9.000000	2.000000

Point of Convergence of Markov Chains with Varying Number of Aperiodic States



Transient Versus Recurrent

```
In [131... def check_transient(mat):
    # Loop on all states to check if all states are connected, if there exist
    for i in range(len(mat)):
        for j in range(len(mat)):
            if(check_connected(mat, i,j)==False):
                return 1
    return 0
```

```
In [651... def check_connected(mat, i, j):
    if((mat[:,i].sum(axis=0)==0)):
        return False
    if(mat[i,j]!=0.0):
        return True
    else:
        y = np.array(np.nonzero(np.array(mat[i,:])))
        y= y[0,:]
        for x in y:
            if(mat[x,j]!=0):
                return True
    return False
```

```
In [647... def transient_count(mat):
    # Create an empty list to store the period of each state in
    periods = []
    # Loop over the number of states
    for i in range(len(mat)):
        period = 0
        # If there exists a path from the state returning to the same state,
        if(mat[i,i]!=0):
            periods.append(1)
            continue
        # Check if the sum of the column is 0 then there exists no path return
        # hence period is undefined
        elif((mat[:,i].sum(axis=0)==0)):
```

```

        periods.append(0)
        continue
    # Check the connected states if they return back to the state in inte
    else:
        # Get the indices of the non-zero values in the row of the state
        y = np.array(np.nonzero(np.array(mat[i,:])))
        y= y[0,:]
        # Loop over the connected states and check their corresponding ro
        for x in y:
            # If the neighboring state is connected to i, then the period
            if(mat[x,i]!=0):
                periods.append(2)
                break
            continue
        # If the period isn't undefined, 1 , or 2, then the period is 3
        else:
            periods.append(3)
            continue
    # Return the number of transient states, that have undefined periods
    return np.count_nonzero(np.array(periods) == 0)

```

```

In [656... def transient(n):
    #create two empty lists to store values in
    tr1 = []
    recurrent = []
    for i in range(1000):
        # randomly generate a matrix and initial state
        p = gen_matrix2(n)
        state = gen_state(n)
        tr = transient_count(p)
        #tr = check_transient(p)
        if(tr==0):
            recurrent.append(convergence(p,state,n))
        elif(tr!=0):
            tr1.append(convergence(p,state,n))
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize = (20, 6))
    sns.histplot(data=remove_outliers(tr1), ax=ax1,color='teal')
    sns.histplot(data = remove_outliers(recurrent), ax=ax2, color='teal')
    ax1.set_title('Transient Chain',fontsize=20)
    ax1.set_xlabel('Convergence Point',fontsize=15)
    ax1.set_ylabel('Count',fontsize=15)
    ax1.grid()
    ax2.set_title('Recurrent Chain',fontsize=20)
    ax2.set_xlabel('Convergence Point',fontsize=15)
    ax2.set_ylabel('Count',fontsize=15)
    ax2.grid()
    fig.suptitle("Point of Convergence of Markov Chains with Transient State
    fig.tight_layout()
    return print_statistics2([tr1, recurrent], ['Transient','Recurrent'])

```

```

In [658... transient(3) #transient function with state or matrix size of 3

```

```

Out[658...

```

	Transient	Recurrent
Count	27.000000	973.000000
Mean	1.111111	50.772867
Stdev	0.320256	235.312660
Minimum	1.000000	1.000000
25%	1.000000	1.000000
50%	1.000000	17.000000

	Transient	Recurrent
75%	1.000000	31.000000
Max	2.000000	2000.000000
Outliers	0.000000	17.000000

Point of Convergence of Markov Chains with Transient State
Versus All Recurrent States

