

## Question\_2

May 4, 2019

```
In [3]: from google.colab import drive
        drive.mount('/content/gdrive')
        path = '/content/gdrive/My Drive/Colab Notebooks/2018701001'
```

Go to this URL in a browser: [https://accounts.google.com/o/oauth2/auth?client\\_id=947318989803-6b](https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6b)

Enter your authorization code:

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Mounted at /content/gdrive

```
In [0]: import matplotlib.pyplot as plt
        def PrecisionGraph(thresh_holds, precision, x, y):
            plt.plot(thresh_holds, precision, label = y)
            plt.ylabel(y)
            plt.title(x + ' Vs ' + y)
            plt.xlabel(x)
            plt.show()
```

```
In [0]: import networkx as nx
        import math
        import sys
```

```
G = nx.DiGraph()
```

```
f = open(path+"/soc-sign-bitcoinalpha.csv","r")
for l in f:
    ls = l.strip().split(",")
    G.add_edge(int(ls[0]), int(ls[1]), weight = float(ls[2])/10) ## the weight should al
f.close()
```

```
# print G[1][10]
# G.node[edge[0]]['pos']
```

```
In [7]: #Initializing fairness and goodness
        fairness = {}
        goodness = {}
```

```

for edge in G.nodes():
    fairness[edge] = 1
    goodness[edge] = 1
t = -1
eps = sys.float_info.epsilon
k=1
j =1
while((k>eps)or(j>eps)):
    t+=1
    k = 0
    j = 0
    for edge in G.nodes():
        sumg = 0
        for inc,outg in G.in_edges(edge):
            sumg += fairness[inc]*G[inc][outg]['weight']
            sumg = float(sumg)/float(len(G.in_edges(edge)))
        k += abs(goodness[edge]-sumg)
        goodness[edge] = sumg
        sumf = 0
        for inc,outg in G.out_edges(edge):
            sumf += abs(G[inc][outg]['weight']-goodness[outg])
            sumf = float(sumf)/float(len(G.out_edges(edge))*2)
            sumf = 1 - sumf
        j += abs(fairness[edge]-sumf)
        fairness[edge] = sumf
    #         print sumf
    print t,k,j

```

```

0 3497.8554411 963.658456249
1 12.9625764386 60.9757329881
2 1.05400392294 1.15686438236
3 0.22105857047 0.215790472701
4 0.0839374871668 0.0801012289815
5 0.0367643927584 0.0357654906231
6 0.0171509328403 0.0169290802701
7 0.0082622739475 0.00822248359515
8 0.0040473007605 0.00404424828756
9 0.00200003223648 0.00200212932031
10 0.000992980847026 0.000994667545205
11 0.000494268330788 0.000495158457613
12 0.000246391447756 0.000246802041708
13 0.000122934832811 0.000123112841764
14 6.13720483879e-05 6.14467220128e-05
15 3.06501128751e-05 3.06808553144e-05
16 1.53112487696e-05 1.53237650969e-05
17 7.65024012787e-06 7.65530171953e-06
18 3.82300098525e-06 3.82503943186e-06
19 1.91066150145e-06 1.91148034212e-06

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20 9.54997311613e-07 9.55325715202e-07  
21 4.77365818513e-07 4.77497397067e-07  
22 2.38629909069e-07 2.38682594911e-07  
23 1.19293787917e-07 1.1931487609e-07  
24 5.96384359605e-08 5.96468747727e-08  
25 2.98158368411e-08 2.98192133208e-08  
26 1.49065665228e-08 1.4907917234e-08  
27 7.45274262443e-09 7.45328321283e-09  
28 3.72615519689e-09 3.72637154467e-09  
29 1.86299112942e-09 1.86307780314e-09  
30 9.31461165143e-10 9.3149588043e-10  
31 4.65716722131e-10 4.65730787269e-10  
32 2.32852882809e-10 2.32858621274e-10  
33 1.16424349328e-10 1.16426757124e-10  
34 5.82113593439e-11 5.82124348725e-11  
35 2.91054194634e-11 2.91059398805e-11  
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37 7.27621435326e-12 7.2765127257e-12  
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39 1.81924614262e-12 1.81943349276e-12  
40 9.09640418545e-13 9.0982776868e-13  
41 4.54893067658e-13 4.55080417794e-13  
42 2.27519392215e-13 2.27706742351e-13  
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44 5.69891356328e-14 5.71764857682e-14  
45 2.85674262024e-14 2.87547763378e-14  
46 1.43565714872e-14 1.45439216226e-14  
47 7.25114412958e-15 7.43849426499e-15  
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[illegible]

[illegible]



[illegible]

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```

```

In [11]: import plotly.plotly as py
import plotly.graph_objs as go

```

```

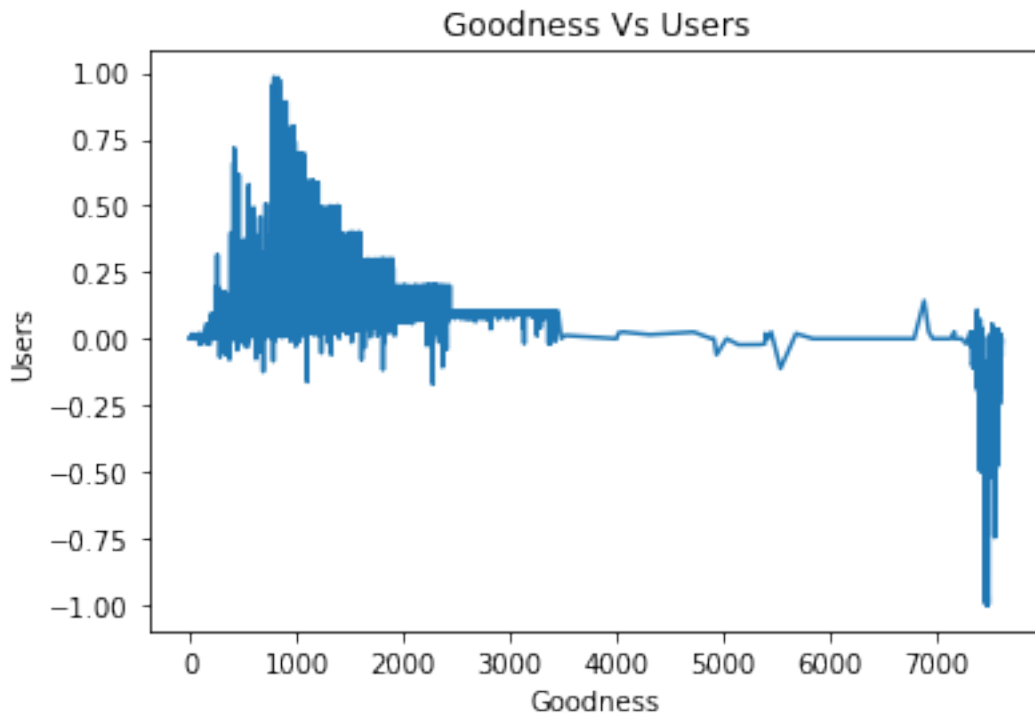
x_axis = []
y_axis = []
for k in goodness.keys():
    x_axis.append(k)
    y_axis.append(round(goodness[k], 4))

```

```

PrecisionGraph(x_axis,y_axis,'Goodness','Users')

```



```

In [16]: x_axis = []
y_axis = []

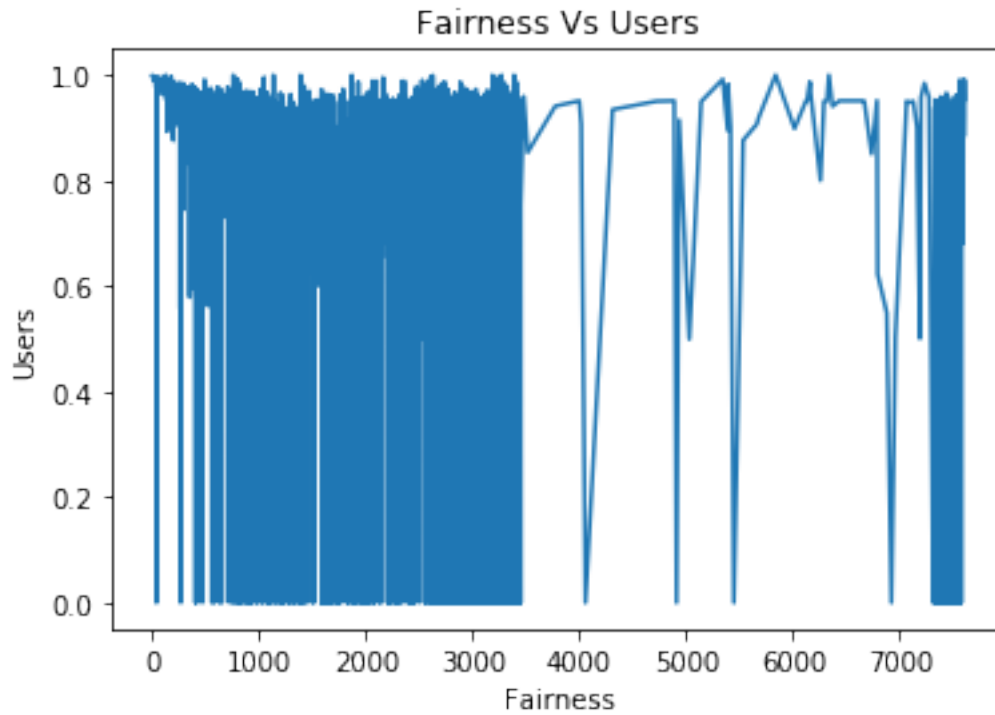
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```

for k in fairness.keys():
    x_axis.append(k)
    y_axis.append(round(fairness[k], 4))

PrecisionGraph(x_axis,y_axis,'Fairness','Users')

```



```

In [17]: #Question 2
import operator
trust_score = {}

def dict_sort_des(diction):
    sorted_d = sorted(diction.items(), key=operator.itemgetter(1),reverse=True)
    return sorted_d

for edge in G.nodes():
    trust_score[edge] = fairness[edge] * goodness[edge]

for i in dict_sort_des(trust_score)[:10]:
    print i[0]

```

791  
828  
932

861  
790  
963  
829  
978  
831  
833

```
In [18]: for i in dict_sort_des(trust_score)[-10:]:  
         print i[0]
```

7481  
7533  
7541  
7538  
7452  
7457  
7449  
7468  
7479  
7456

```
In [24]: #Question -3  
         largest = max(nx.strongly_connected_components(G), key=len)  
         print len(largest)  
         print len(G.nodes)
```

3235  
3783

```
In [0]: # Function for Calculating Clustering Co-efficients.  
def clusteringCoeff(tempGraph):  
    degClusDict = dict()  
    for eachNode in tempGraph.nodes():  
        degClusDict[eachNode] = (tempGraph.degree(eachNode), nx.clustering(tempGraph, eachNode))  
    final_Dict = dict()  
    for key in degClusDict.keys():  
        if degClusDict[key][0] in final_Dict:  
            final_Dict[degClusDict[key][0]].append(degClusDict[key][1])  
        else:  
            final_Dict[degClusDict[key][0]] = [degClusDict[key][1]]  
    for key in final_Dict:  
        final_Dict[key] = float(sum(final_Dict[key]))/len(final_Dict[key])  
    return final_Dict  
  
k_Ck = clusteringCoeff(G)
```

```

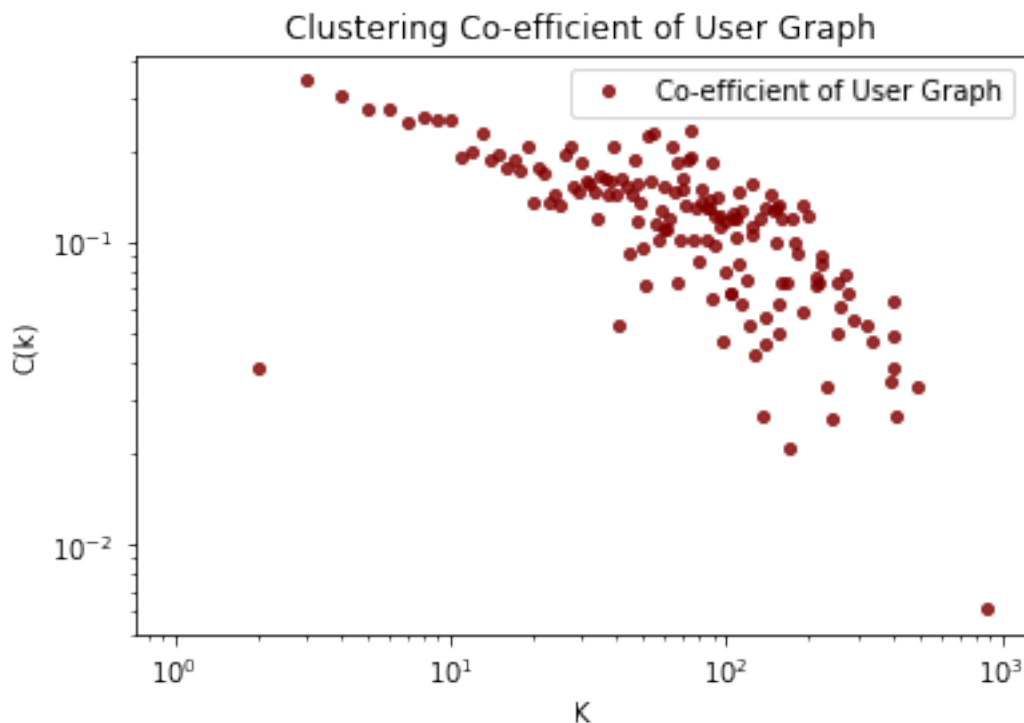
In [21]: import matplotlib.pyplot as plt
          %matplotlib inline
          def getXYAxis(temp_Ck,maxDegree):
              plot_Ck_y = []
              plot_k_x = []
              for i in range(maxDegree+1):
                  plot_k_x.append(i)
                  if i in temp_Ck:
                      plot_Ck_y.append(temp_Ck[i])
                  else:
                      plot_Ck_y.append(float(0))
              return plot_k_x,plot_Ck_y

          k_maxDegree = max(k_Ck.items(), key=operator.itemgetter(0))[0]
          k_plot_Ck_x,k_plot_Ck_y = getXYAxis(k_Ck,k_maxDegree)

          plt.yscale('log')
          plt.xscale('log')
          plt.plot(k_plot_Ck_x, k_plot_Ck_y, label='Clustering Coefficient Graph',linewidth=0, marker='o')
          plt.title("Clustering Co-efficient of User Graph")
          plt.ylabel("C(k)")
          plt.xlabel("K")
          plt.legend(['Co-efficient of User Graph'],loc = 'upper right')

Out[21]: <matplotlib.legend.Legend at 0x7fe0be00d3d0>

```



```

In [22]: asrt_k = nx.k_nearest_neighbors(G)
          maxAssrt = max(asrt_k.items(), key=operator.itemgetter(0))[0]
          asrt_k

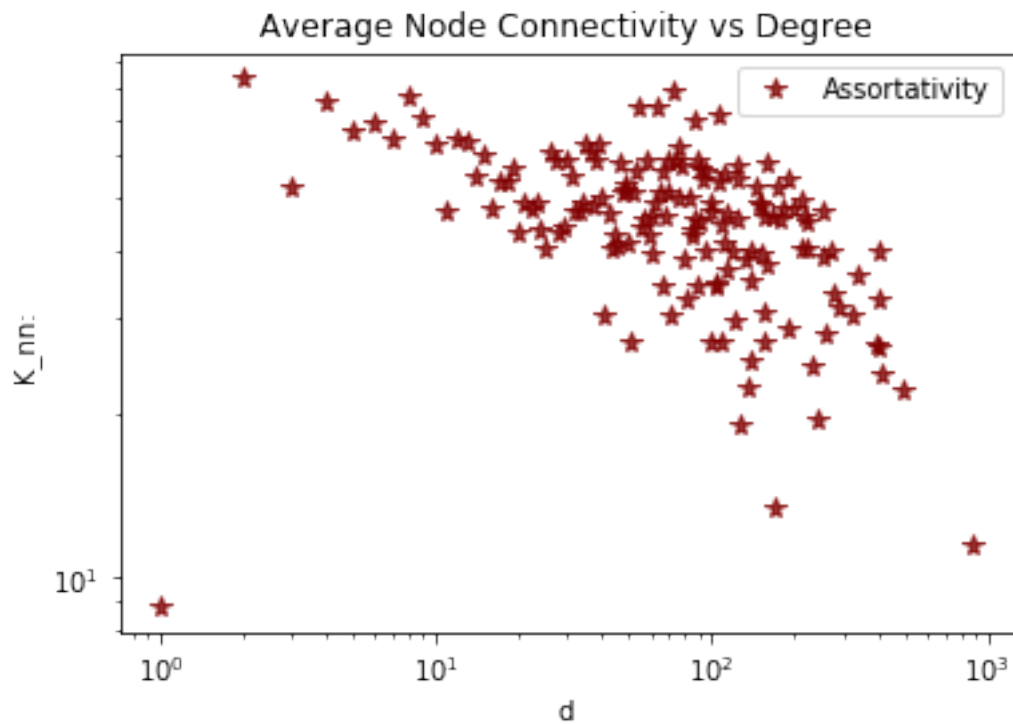
          asrt_k_x_axis,asrt_k_y_axis = getXYAxis(asrt_k,maxAssrt)
          plt.yscale('log')
          plt.xscale('log')
          plt.plot(asrt_k_x_axis, asrt_k_y_axis, label='Assortativity of Graph',linewidth=0, marker='*')
          plt.title("Average Node Connectivity vs Degree")
          plt.ylabel("K_nn:")
          plt.xlabel("d")
          plt.legend(['Assortativity'])

```

```

Out[22]: <matplotlib.legend.Legend at 0x7fe0c0a262d0>

```



```

In [0]:

```

To interpolate the scores to a single value, we multiply both fairness and goodness scores.

The fairness of a user is same as the reliability of the user. Thus, the users' fairness is same as reliability score.