Module IV - Basic Analysis

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NEW YORK UNIVERSITY

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Agenda for Module IV

Loading data from multiple sources

- Local network data files
- Connecting to a database
- Building directly from the Internet

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Brief review of Python dictionaries

- Why is the `dict` so useful?
- How `NetworkX` utilizes it?

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Running basic centralities

- Degree, Closeness, Betweeness Eigenvector
- Calculating degree distribution
- Plotting statistics using `matplotlib`
- Calculating cliques, clustering and transitivity

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- Writing network data
- Saving network analysis statistics

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Basic visualization

- Review of `NetworkX`'s plotting algorithms
- Adding analysis to visualization

Loading a network file

As we have seen, one of the main advantages of working with NetworkX is that it can read many different network formats

- For those that are unfamiliar with working at the **command-line**, however, the process can be confusing

NX syntax for loading a file

$$\begin{array}{cccc} >>> G & = \quad \text{read\_format}(\text{``path/to/file.txt''}, & & \ldots \mathit{options} \ldots) \\ \uparrow & & \uparrow & \uparrow \\ \text{Net variable} & & \text{NX function, file directory path} & \text{Graph type, nodes type, etc.} \end{array}$$

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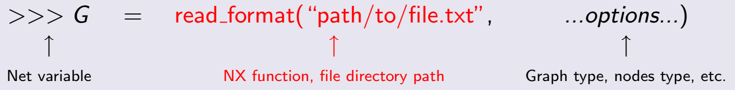

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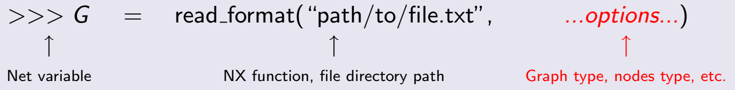

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Let's try!

- We will load the edge list of Hartford drug users network
- Specify that the network be a directed graph, and the nodes be integers
- Use `info()` to check that data has been loaded correctly

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- Specify that the network be a directed graph, and the nodes be integers
- Use `info()` to check that data has been loaded correctly

It’s time to fire up your console and load Python!

Loading the Hartford drug users network

Starting NetworkX and loading data

```
>>> from networkx import *
>>> hartford=read_edgelist("../../data/hartford_drug.txt",create_using=DiGraph(),nodetype=int)
>>> info(hartford)
Name:
Type:                   DiGraph
Number of nodes:        212
Number of edges:        337
Average in degree:      1.5896
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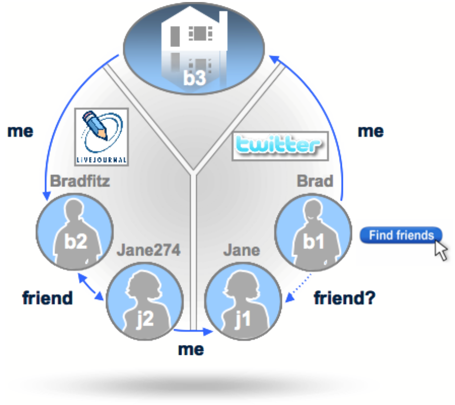
Some formats may have more or less options, **always check the documentations!**

Building a network from a database

As data sets become larger and persistently changing, it may make more sense to store them in a database rather than a single file

- As we have seen, Python provides binding to many modern database frameworks

Building the social network among LiveJournal users



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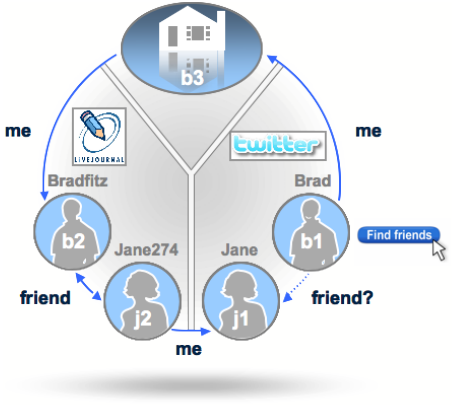

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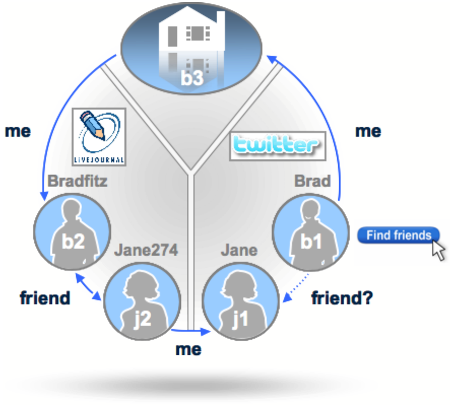

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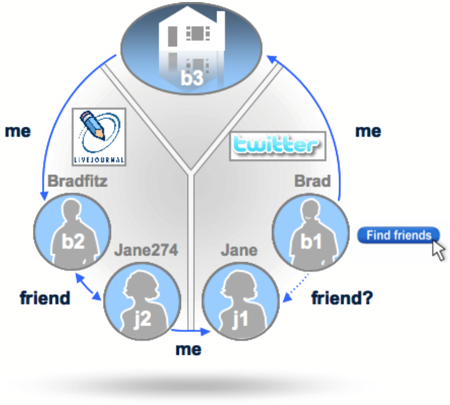

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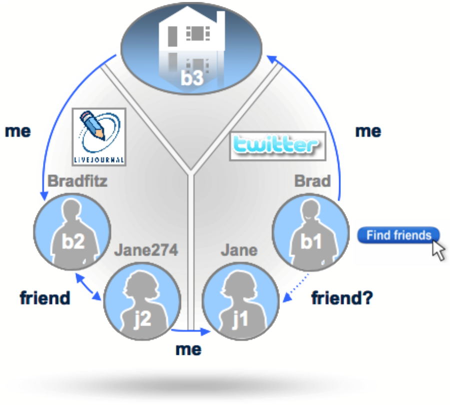

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  - $k = 3$

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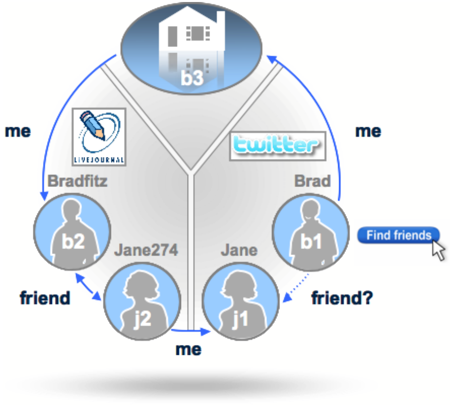

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  - Seed: imichaeldotorg.livejournal.com
  - $k = 3$
- Note the low value of k

The code, part 1

Loading the libraries and setting things up

```
from cjson import *
from urllib import *
from networkx import *
from time import *
from scipy import array,unique
...
if __name__ == "__main__":
    seed_url=‘‘http://imichaeldotorg.livejournal.com"
    sg=get_sg(seed_url)
    net,newnodes=create_egonet(sg)
    info(net)
```

Get the JSON from SocialGraph

```
def get_sg(seed_url):
  sgapi_url="http://socialgraph.apis.google.com/lookup?q="+seed_url+"&edo=1&edi=1&fme=1&pretty=0"
  try:
      furl=urlopen(sgapi_url)
      fr=furl.read()
      furl.close()
      return fr
  except IOError:
      print "Could not connect to website"
      print sgapi_url
      return
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```

```
Name:                   [‘http://imichaeldotorg.livejournal.com/’]
Type:                   DiGraph
Number of nodes:        5
Number of edges:        5
Average in degree:      1.0
Average out degree:     1.0
```

Get the JSON from SocialGraph

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def get_sg(seed_url):
  sgapi_url="http://socialgraph.apis.google.com/lookup?q="+seed_url+"&edo=1&edi=1&fme=1&pretty=0"
  try:
      furl=urlopen(sgapi_url)
      fr=furl.read()
      furl.close()
      return fr
  except IOError:
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      return
```

Build egonet and snowball

Creating the egonet

```
def create_egonet(s):
    try:
        raw=decode(s)
        G=DiGraph()
        pendants=[]
        n=raw[’nodes’]
        nk=n.keys()
        G.name=str(nk)
        pendants=[]
        for a in range(0,len(nk)):
            for b in range(0,len(nk)):
                if a!=b:
                    G.add_edge(nk[a],nk[b])
        for k in nk:
            ego=n[k]
            ego_out=ego[’nodes_referenced’]
            for o in ego_out:
                G.add_edge(k,o)
                pendants.append(o)
            ego_in=ego[’nodes_referenced_by’]
            for i in ego_in:
                G.add_edge(i,k)
                pendants.append(i)
        pendants=array(pendants,dtype=str)
        pendants.flatten()
        pendants=unique(pendants)
        return G,pendants
    except DecodeError:
    ...
    except KeyError:
```

Rolling the snowball

```
def snowball_round(G,seeds,myspace=False):
    t0=time()
    if myspace:
        seeds=get_myspace_url(seeds)
    sb_data=[]
    for s in range(0,len(seeds)):
        s_sg=get_sg(seeds[s])
        new_ego,pen=create_egonet(s_sg)
        for p in pen:
                sb_data.append(p)
        if s<1:
            sb_net=compose(G,new_ego)
        else:
            sb_net=compose(new_ego,sb_net)
        del new_ego
        if s==round(len(seeds)*0.2):
            sb_net.name=’20% complete’
            sb_net.info()
            print ’AT: ’+strftime(’%m/%d/%Y, %H:%M:%S’, gmtime())
            print ’’
    ...
    # More time keeping, probably a MUCH better way to do this
    sb_data=array(sb_data)
    sb_data.flatten()
    sb_data=unique(sb_data)
    sb_net.info()
    return sb_net,sb_data
```

Build the whole network

Step	Nodes	Edges	Mean Degree	Density
Seed	5	5	2.0	0.25
$k = 2$	75	115	3.0	0.02
$k = 3$	4,938	8,659	3.5	$3.6(10^{-4})$

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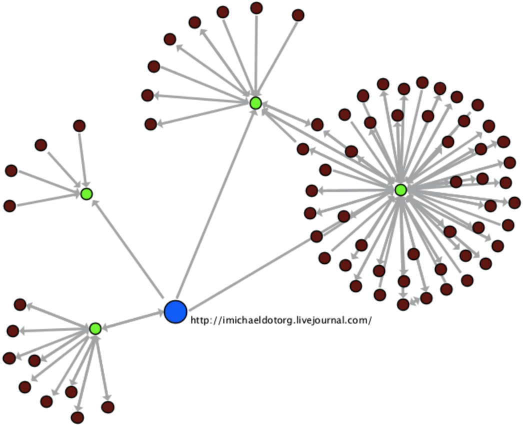
- Large jump after first snowball



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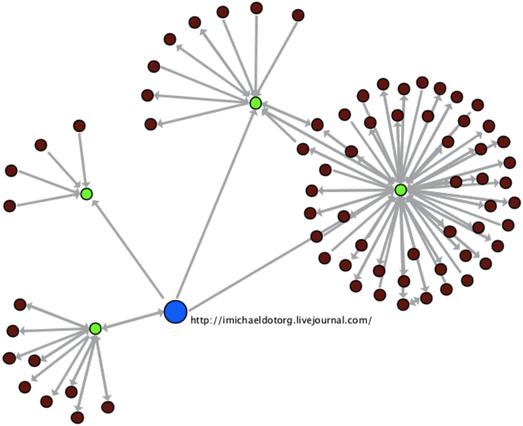
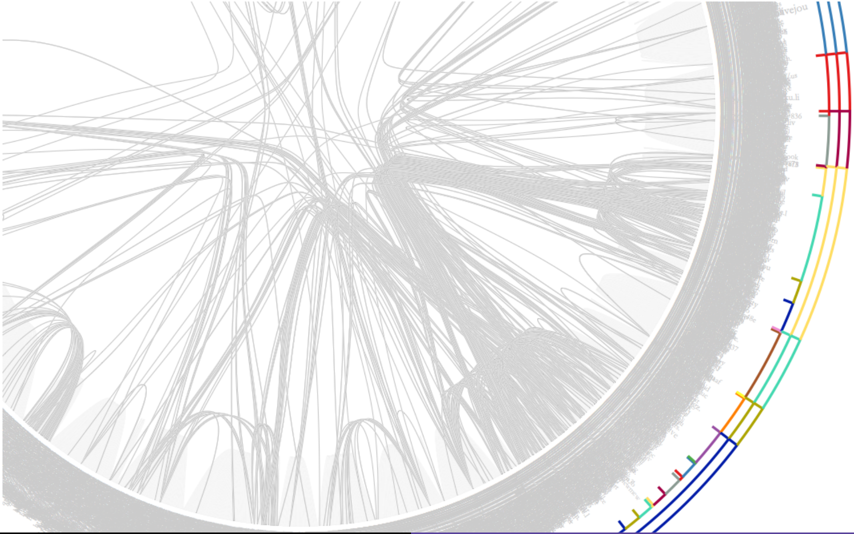
- Our seed is abnormally isolated, with only four neighbors
- Large jump after first snowball
- Massive structural leap at $k = 3$



The full network

To get a feeling for the size of the full network...



Python Dictionaries

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Working with the dict type

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# Can retrieve the keys and values as Python lists (vector)
>>> fruit_dict.keys()
["orange","apple","banana"]
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# Or create a (key,value) tuple
>>> fruit_dict.items()
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Now, try creating a dict of your own

Using dictionaries for network analysis

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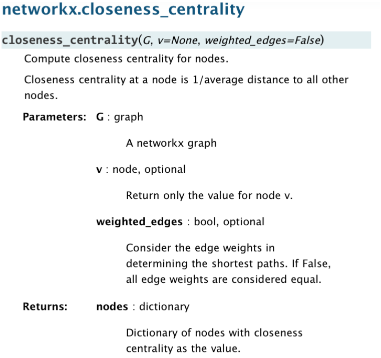

networkx.closeness_centrality

`closeness_centrality`(*G*, *v=None*, *weighted_edges=False*)

Compute closeness centrality for nodes.

Closeness centrality at a node is 1/average distance to all other nodes.

Parameters: **G** : graph

A networkx graph

v : node, optional

Return only the value for node v.

weighted_edges : bool, optional

Consider the edge weights in determining the shortest paths. If False, all edge weights are considered equal.

Returns: **nodes** : dictionary

Dictionary of nodes with closeness centrality as the value.

`NetworkX`'s metric's make extensive use of the dict type

- In this case the key→value mapping is of the form: {`node_label: metric`}

Let's look at an example:

In-degree centrality of Hartford data

```
>>> in_cen=in_degree_centrality(hartford)
>>> in_cen
{1: 0.014218009478672987, 2: 0.018957345971563982,...
...
90: 0.0047393364928909956, 293: 0.0}
```

We can see that node #90 has in-degree centrality 0.0047

- But we can do so much more!

Using dictionaries for network analysis

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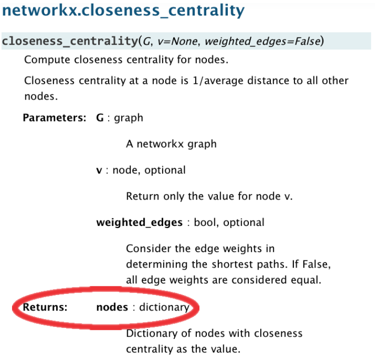

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We can see that node #90 has in-degree centrality 0.0047

- But we can do so much more!

Running multiple measures

For our first analysis in NetworkX, we will do some basic network manipulation, then run multiple measures to find highest centrality nodes

- First, we will need to convert to an undirected network, and extract the main component

Find main component & symmetrize

```
# Many of the centrality metrics require undirected graphs, so we will symmetrize
>>> hartford_ud=hartford.to_undirected()
# The network also has many small components, but for
# this analysis we are interested in the largest
>>> hartford_mc=hartford_main=connected_component_subgraphs(hartford_ud)[0]
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Next, we will calculate multiple measures

Computing multiple centralities

```
# Betweenness centrality
>>> bet_cen=betweenness_centrality(hartford_mc)
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Finding most central actors

To find the most central actors we will use Python's list comprehension technique to do basic data manipulation on our centrality dictionaries

Function for finding most central actor

```
def highest_centrality(cent_dict):
    """Returns node key with largest value from
    NX centrality dict"""
    # Create ordered tuple of centrality data
    cent_items=cent_dict.items()
    # List comprehension!
    cent_items=[(b,a) for (a,b) in cent_items]
    # Sort in descending order
    cent_items.sort()
    cent_items.reverse()
    return cent_items[0][1]
```

Now, just ask for the answer

Finding Most central actors

```
>>>  print("Actor "+str(highest_centrality(bet_cen))+" has the highest Betweenness centrality")
Actor 82 has the highest Betweenness centrality
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List comprehension

- Given a dict: `d={1: 0.15, 2: 0.67}`
- `d.items()` → `[(1,0.15),(2,0.67)]`
- `d=[(b,a) for (a,b in d)]` → `[(0.15,1),(0.67,2)]`

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Recall Python's scientific computing trinity: NumPy, SciPy and matplotlib

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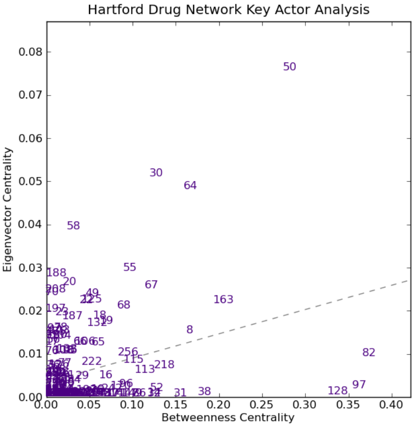

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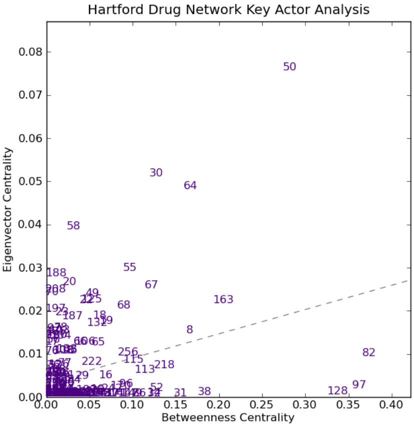

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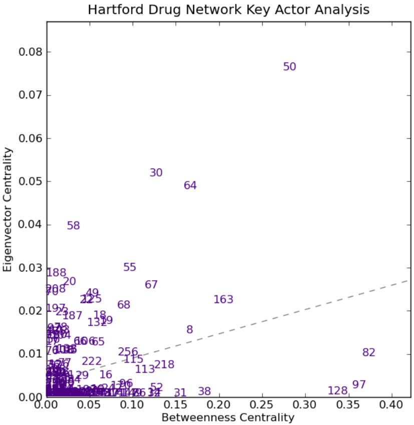

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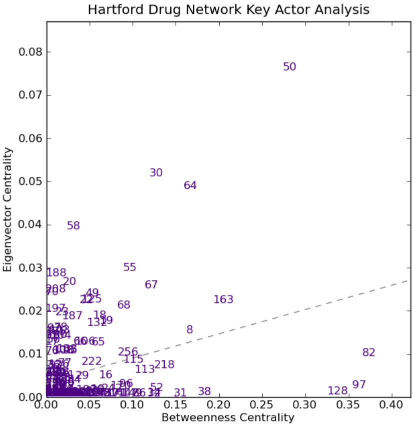

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1. Create a matplotlib figure
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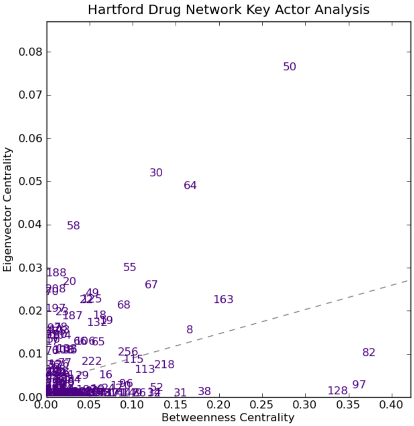

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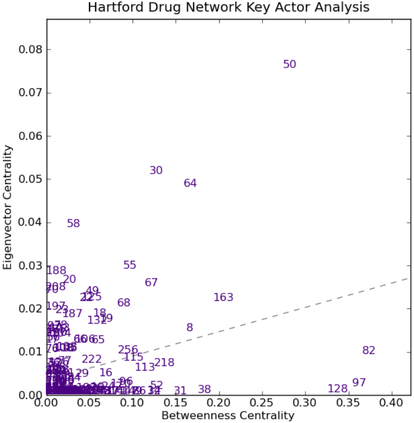

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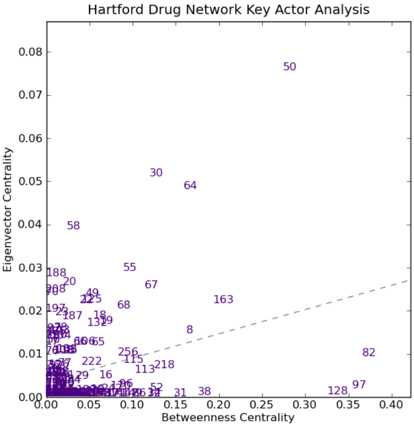

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1. Create a matplotlib figure
2. Plot each node label as a point
3. Add a "best fit" line
4. Add axis and title labels
5. Save figure as a PNG file

Creating a key actor plot in matplotlib

The centrality_scatter function, part one

```
def centrality_scatter(met_dict1,met_dict2,path="",ylab="",xlab="",title="",reg=False):
    # Create figure and drawing axis
    fig=P.figure(figsize=(7,7))
    ax1=fig.add_subplot(111)
    # Create items so actors can be sorted properly
    met_items1=met_dict1.items()
    met_items2=met_dict2.items()
    met_items1.sort()
    met_items2.sort()
    # Grab data
    xdata=[(b) for (a,b) in met_items1]
    ydata=[(b) for (a,b) in met_items2]
    # Add each actor to the plot by ID
    for p in xrange(len(met_items1)):
        ax1.text(x=xdata[p],y=ydata[p],s=str(met_items1[p][0]),color="indigo")
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- Create a canvas to draw on
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- Create a canvas to draw on
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...
    # If adding a best fit line, we will use NumPy to calculate the points.
    if reg:
        # Function returns y-intercept and slope.  So, we create a function to
        # draw LOBF from this data
        slope,yint=polyfit(xdata,ydata,1)
        xline=P.xticks()[0]
        yline=map(lambda x: slope*x+yint,xline)
        # Add line
        ax1.plot(xline,yline,ls=’--’,color=’grey’)
    # Set new x- and y-axis limits to data
    P.xlim((0.0,max(xdata)+(.15*max(xdata))))   # Give a little buffer
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- Add a best fit line
- Resize figure to fit data
- Add labels, and save the figure as a PNG file

Exporting network data and analytics

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Next, we will review how to save data in different formats and export metrics to a CSV file using the Hartford drug net data

Saving network data in different formats

The syntax for exporting network data follows exactly the syntax for loading it

NX syntax for loading a file

>>> write_format(G, "path/to/file.txt", *...options...*)

↑ NX function, net variable

↑ File to be written

↑ Nodes/edge data, etc.

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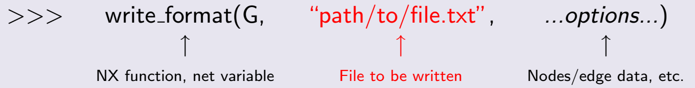

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