This tutorial is Part 2 of an introduction to social network analysis in Python. It covers how to sample and visualize network data. The primary example used for replication is Adamic and Glance's (2005) paper on relationships between political blogs ahead of the 2004 election. The paper is available here and is the source of all figures included below. We use the GML file available here (<a href="http://www.thomaspadilla.org/data/network/polblogs/polblogs.gml">http://www.thomaspadilla.org/data/network/polblogs/polblogs.gml</a>) or here (<a href="http://www.thomaspadilla.org/data/network/polblogs/polblogs.gml">http://www.thomaspadilla.org/data/network/polblogs/polblogs.

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Let's get started! First, we need to import all of the packages we'll use to do our analysis.

```
In [1]: import pandas as pd  # For analyzing tabular data import numpy as np  # For working with arrays and numerical operations import networks as nx  # For network data specifically from networks.drawing.nx_agraph import graphviz_layout # ...and graphing network data import matplotlib.pyplot as plt from pyvis import network as pv  # For making interactive plots import random # For generating random numbers

%matplotlib inline
```

# 1 Importing external data files

We will be using a dataset from Adamic and Glance's (2005) paper: The political blogosphere and the 2004 US election: Divided they blog.

The paper built a dataset of political blogs as follows:

- They compiled a list of important blogs from blog curation sites (e.g. BlogCatalog).
- They crawled the front pages of these blogs and got all other linked blogs on these pages
- If the other blog had at least 17 citations in the dataset, they kept it and got its links.
- They labeled the political orientation of the blogs using the blog curation sites and their own inspections.

The final dataset had

- 759 liberal blogs
- 735 conservative blogs

Key findings from this analysis:

"91% of links originating within either the conservative or liberal communities stay within that community...Conservative blogs show a greater tendency to link."

 $\textbf{Reference: } \underline{\textbf{https://networkx.github.io/documentation/stable/reference/readwrite/index.html}. (\underline{\textbf{https://networkx.github.io/documentation/stable/reference/readwrite/index.html}). (\underline{\textbf{https://networkx.github.i$ 

```
First, let's practice importing files from external data sources. There are many different formats for disseminating network data, but some helpful ones supported by NetworkX include:

nx.read_gml(filepath)  # GML

nx.read_edgelist(filepath, delimiter=',')  # A delimited edgelist

nx.from_pandas_edgelist(df)  # Pandas dataframe in edge list format
nx.from_pandas_adjacency(df)  # Pandas dataframe in adjacency matrix format
```

We'll get started with the dataset of blog links.

Note: Because some edges are duplicated, we had to modify the original file by adding a line to indicate that it is a multigraph. So, the dataset on this server is not perfectly identical to the original.

```
In [2]: # Let's use NetworkX's read_gml to bring in the raw data file
G = nx.read_gml("data/polblogs.gml")
G
```

Out[2]: <networkx.classes.multidigraph.MultiDiGraph at 0x154b76e5470>

```
In [3]: # As discussed, note that the graph above is a multigraph
# Let's now convert it from a multigraph to a directed graph
P = nx.DiGraph(G)
```

```
In [4]: # And, we inspect
print(nx.info(P))
```

Name: Type: DiGraph Number of nodes: 1490 Number of edges: 19025 Average in degree: 12.7685 Average out degree: 12.7685

The dataset does not seem to be a perfect match for the paper. For example, we have 1940 links while they had 1494. But, it's close. We can also confirm that our degree counts roughly match those reported for Daily Kos (338), Eschelon (264), and Instapundit (277).

```
In [5]: # Code to get all blog names containing a given keyword: [i for i in list(P.nodes) if 'instapundit' in i]
# Let's check if individual blog degrees match:
P.in_degree(['dailykos.com', 'atrios.blogspot.com', 'instapundit.com'])
```

Out[5]: InDegreeView({'dailykos.com': 337, 'atrios.blogspot.com': 263, 'instapundit.com': 276})

# 2 Downsampling graphs

We can see that the graph is (relatively) large and pretty well-connected: 1490 nodes and 19,025 edges. This is not actually "large" by network standards (Facebook has 1.7 billion users) but on my computer the plots are still running slow.

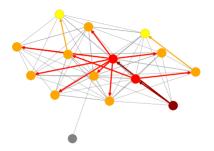
Since we will be making many plots, and since it's generally helpful for large graphs, let's learn to downsample. I will demonstrate two different approaches.

# 2.1 Snowball sample

One common method for sampling graphs is snowball sampling. The basic idea is as follows:

- 1. Start with set of seed nodes.
- 2. Add any friends of the seed nodes.
- 3. Add any friends of the friends of the seed nodes.
- 4. Add any friends of the friends of the (friends of the...) seed nodes.

In [6]:



```
We will use a few helper functions, including some from Python's random package:

nx.single_source_shortest_path(G, source, cutoff=n)  # Get all shortest paths from source node within distance n

nx.bfs_tree(G, source, depth_limit=n)  # Conduct a breadth-first search of depth n

S = G.subgraph(...)  # Select a subgraph

random.seed(n)  # Set a "seed" for the random number generator. This ensures that your code is replicable.

random.sample([...], n)  # Choose n items from a list of items
```

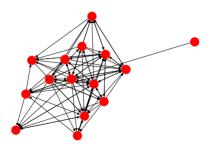
## 2.1.1 Snowball sampling with single-source-shortest-paths

Actually, last week we learned an algorithmic approach to implementing this with NetworkX. Remember that we had a function, single\_source\_shortest\_path, that would give a list of all shortest paths from a source node. Well, that function takes an optional argument, cutoff, that limits the maximum length of the shortest paths returned.

This can help us find our sample: we start from our source node, and then walk away in all directions until we hit the cutoff.

Let's try this for the blogger Matt Yglesias.

In [8]: # Let's take the subgraph of P containing this sample
S = P.subgraph(sample)



#### 2.1.2 Snowball sampling with breadth-first search

Note that this is equivalent to a breadth-first tree search on the graph.

```
In [9]: # Let's do a BFS from the source with a depth of 2
sample = nx.bfs_tree(Q, source, depth_limit=2 )

# Let's collect the subgraph
S = P.subgraph(sample)

# Let's confirm that it's the same size
len(sample)
```

Out[9]: 15

# 2.2 Node and edge samples

Let's try another strategy, just for fun.

- 1. We will first randomly sample 500 nodes from the graph (reduce the number of nodes).
- 2. Then, we will randomly sample 500 edges from these nodes (reduce the number of edges).
- 3. Finally, we will keep only the largest connected component (reduce the number of small isolated components).

```
In [10]: # Set the seed for a random number
  random.seed(1)
```

random\_nodes = random.sample(P.nodes, 500)
# Get the subgraph containing of P these nodes
R = P.subgraph(random\_nodes)

print(nx.info(R))

Name: Type: DiGraph Number of nodes: 500 Number of edges: 1947 Average in degree: 3.8940 Average out degree: 3.8940

In [12]: # Step 2 -----

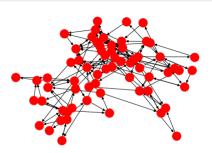
# Choose a random sample of p's edges
random\_edges = random.sample(R.edges, 500)

# Get the subgraph containing of P these edges
R = P.edge\_subgraph(random\_edges)

In [13]: # Step 3 -----

# Get the biggest connected component  $R = \max(nx.strongly\_connected\_component\_subgraphs(R), key=len)$ 

nx.draw(R)



# 3 Plotting

Exercise: Now, it's time to see what we've got! Before we start, let's practice drawing a graph of our own. Try plotting the following adjacency matrix:

#### In [14]:

Out[14]:

|   | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| 2 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| 3 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| 8 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| 9 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

# 3.1 Graph Layouts

Reference: <a href="https://networkx.github.io/documentation/stable/reference/drawing.html#module-networkx.drawing.layout">https://networkx.github.io/documentation/stable/reference/drawing.html#module-networkx.drawing.layout</a> (https://networkx.github.io/documentation/stable/reference/drawing.html#module-networkx.drawing.layout)

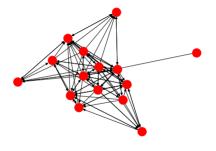
A basic challenge for plotting networks is how to lay out the nodes and edges.

- One option is to use a fixed layout design, such as circular layouts (which put all nodes in a circle) or geographic layouts (which put nodes at their geographic location on a map).
- An alternative is to use an **algorithm** to determine the layout of nodes. Common classes of algorithms are:
- Force-directed layouts: These algorithms generally balance two forces: a baseline repulsion between all nodes, and a countervailing attraction between connected nodes.
- Spectral layouts: These algorithms perform dimensionality reduction to divide the graph into different clusters.

You might have to experiment a bit to get the layout you want. Let's try it!

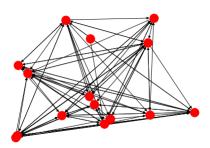
#### 3.1.1 Default (spring) layout

In [15]: # We start with the default graph.
nx.draw(S)



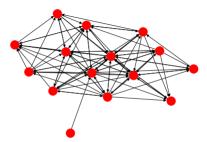
# 3.1.2 Random layout

In [16]: # Actually, it's not bad! If we drew it with a random layout, it would look worse... nx.draw\_random(S)



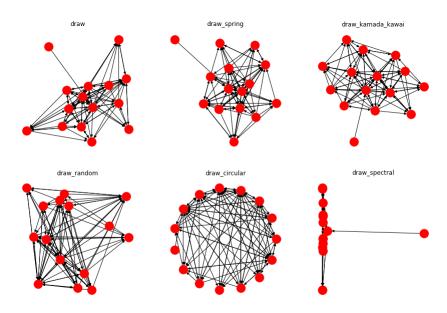
#### 3.1.3 Kamada-Kawai (force-directed) layout

In [17]: # Maybe there are some other alternatives?
 nx.draw\_kamada\_kawai(S)



#### 3.1.4 Layouts overview

#### In [18]:



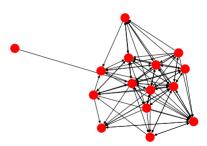
# 3.1.5 Tuning graph layouts

We can also tweak individual algorithms. Before we start with that, though, we need to understand a little bit about NetworkX.

- Above, we have seen NetworkX's draw commands that directly incorporate the desired layout, e.g. draw\_spring .
- However, we can also plot graphs with a given layout in two steps:
  - 1. Request the layout positions.
  - 2. Pass the layout positions to the draw command.

To tweak the positions, you'll need to read the documentation to see what parameters are available to you. For example, let's look into the spring\_layout  $(\underline{https://networkx.github.io/documentation/stable/reference/generated/networkx.drawing.\underline{layout.spring\_layout.html}).$ 

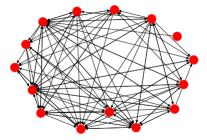
In [19]: # To tweak the layout, we'll need to work in two steps
pos = nx.spring\_layout(S) # First, we run the algorithm to get the positions
nx.draw(S, pos=pos) # Next, we plot the graph using those positions



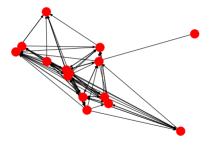
In [20]: # For example, we can scale it down in size ...
pos = nx.spring\_layout(S, scale=0.01)
nx.draw(S, pos=pos)



In [21]: # ... we can push nodes apart ...
pos = nx.spring\_layout(S, k=5)
nx.draw(S, pos=pos)



In [22]: # ...or pull them together
pos = nx.spring\_layout(S, k=0.01)
nx.draw(S, pos=pos)



# 3.2 Styling the plot aesthetic

For now, let's stick with the default Kamada-Kawai layout. We will set this one time and then use it subsequently below.

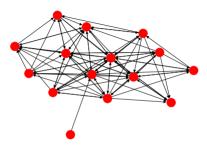
In [23]: # Set the positions for the rest of this section
pos = nx.kamada\_kawai\_layout(S)

# 3.2.1 Plotting the default

Below, we can see the default plot that we've grown used to generating. But now, it takes the pos argument which determines the node positions.

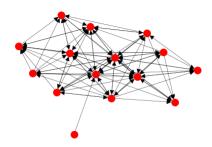
We can pass other arguments to the command to change other aspects of the graph styling:

In [24]: # Draw the default
nx.draw(S, pos=pos)



# 3.2.2 Change sizes of nodes, edges, or arrows

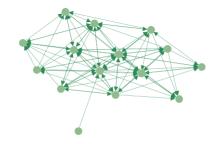
```
In [25]: nx.draw(S, pos=pos, node_size=200, # Change size of node width=0.5, # Change width of edge arrowsize=20 # Change size of arrow
)
```



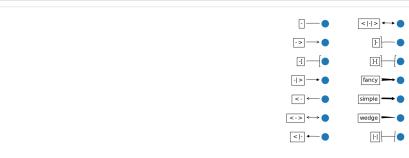
#### 3.2.3 Change colors of nodes or edges







# 3.2.4 Change styling of nodes or arrows







# ▼ 3.2.5 Turn plot features on and off

```
In [28]: nx.draw(S, pos=pos, node_size=200, width=0.5, node_size=200, width=0.5, node_color="darkseagreen", edge_color='seagreen', node_shape='s', "

arrows=False, # Control whether arrow is shown with_labels=True # Control whether plot is labeled
)
```

```
angrybear blogspot.com

j.bradford-delong net/moyable type
harkschmitt.rypepad com/decembrist

peak org/mt
atrios blogspot.com
washingtormenthly.com
newdonkey.

pandagon.net
prospect org/weblog
matthewyglesias.com
```

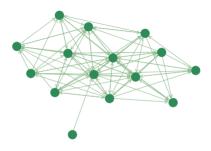


# 3.3 Drawing attention to selected features

Now, we'll show how you can select and emphasize certain features. For example, you might want to tell a story about a given node.

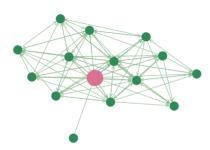
Essentially, the easiest way to do this is:

- 1. Get the positions of the graph layout.
- 2. Plot the underlying graph and nodes.
- 3. Layer your styling on top.



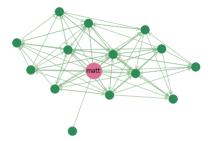
3.3.1 Drawing selected nodes

Out[31]: <matplotlib.collections.PathCollection at 0x154bbf7f470>



#### 3.3.2 Drawing selected node labels

```
In [32]: # Let's plot the underlying graph
nx.draw(S, pos=pos,
node_size=390,
node_color='seagreen',
edge_color='darkseagreen',
arrowstyle='->',
arrowstyle='--',
arrowstyle='--
```



## 3.3.3 Drawing selected edges

```
In [33]:
# Let's plot the underlying graph
nx.draw(s, posspos,
node_size=300,
node_size=300,
node_size=300,
node_size=300,
node_size=300,
node_size=300,
node_size=30)
# We can choose a List of nodes we want to emphasize (in this case, one of Matt Yglesias' pages)
selected_nodes = ['yglesias.typepad.com/matthew']

# Let's resize and recolor the node(s) of interest
nx.draw_networkx_nodes(s, posspos,
node_list=selected_nodes,
node_clore 'palevioletred',
node_size=1000)

# We can create a dictionary of nodes to Lobel, and the Lobels we want
selected_labels = ('yglesias.typepad.com/matthew': "matt')

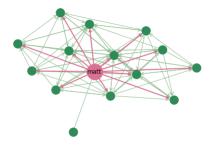
# Let's add these Lobels
nx.draw_networkx_labels(s, posspos,
labels=selected_labels, # Dictionary of nodes to Label

# Note can create a List of edges we want to plot <- in this case, all of Matt's
selected_edges = list(S.edges(['yglesias.typepad.com/matthew']))

# We can create a list of edges we want to plot <- in this case, all of Matt's
selected_edges = list(S.edges(['yglesias.typepad.com/matthew']))

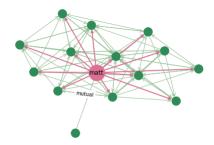
# We can plot only these edges
nx.draw_networkx_edges(S, pos=pos,
edge_clore = 'palevioletred',
width=2)

plt.show()
```



3.3.4 Drawing selected edge labels

```
In [34]: # Let's plot the underlying graph
         arrowsize=15
         # We can choose a list of nodes we want to emphasize (in this case, one of Matt Yglesias' pages)
selected_nodes = ['yglesias.typepad.com/matthew']
          # Let's resize and recolor the node(s) of interest
nx.draw_networkx_nodes(S, pos=pos,
                                 nodelist=selected_nodes, # List of nodes to alter with new styling
node_color = 'palevioletred',
                                 node_size=1000)
          # We can create a dictionary of nodes to Label, and the Labels we want
selected_labels = {'yglesias.typepad.com/matthew': "matt"}
          # Let's add these Labels
          nx.draw_networkx_labels(S, pos=pos,
                                                               # Dictionary of nodes to label
                                   labels=selected_labels,
                                   font_size=12)
          # We can create a list of edges we want to plot <- in this case, all of Matt's
          selected_edges = list(S.edges(['yglesias.typepad.com/matthew']))
          # We can plot only these edges
                                 eagelist=selected_edges, # List of edges to restyle
edge_color = 'palevioletred',
width=2)
          nx.draw_networkx_edges(S, pos=pos,
    edgelist=selected_edges,
          # -----
# We can create a dictionary of edges we want to label, and their labels
          selected_edge_labels = {("pandagon.net", "prospect.org/weblog"): "mutual"}
          plt.show()
```



#### 3.4 Illustrating discrete attributes

Of course, we might want to systematically render attributes of our graph. For example, in our dataset, there is an attribute called "value", which is set to 0 if the blog is liberal and 1 if it is conservative.

Let's drop Matt's blog network and switch back to the sample we previously made, R.



Exercise: Let's tidy up the graph a bit. How would you..

- make the size of the nodes to be 100
- make the color of the edges to be grey
- make the style of arrows to be a "v" instead of a triangle?

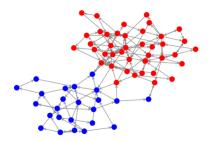
**Answer**: pos = nx.kamada\_kawai\_layout(R) nx.draw(R, pos=pos, node\_size=100, edge\_color='gray', arrowstyle="->")

# 3.4.1 Coloring nodes by label

Let's highlight groups of nodes by changing the label color.

```
In [36]: # We can see that each node has an attribute caleld "value" with political affiliation
                           # It also has information about the source of the bloa
                          R.nodes.data()
R.nodebataView(('jquinton.com': {'value': 1, 'source': 'labeledManually'), 'cbcbcbb.blogspot.com': {'value': 1, 'source': 'labeladManually'}, 'demagogue.blogspot.com': {'value': 0, 'source': 'LeftyDirectory, eTalkingHead'}, 'crank yneocon.com/crankyneocon': {'value': 1, 'source': 'labeladManually'}, 'nomespunbloggers.blogspot.com': {'value': 1, 'source': 'labeladManually'}, 'value': 1, 'source': 
 In [37]: # Let's extract political affiliation as a dictionary
political_affil = nx.get_node_attributes(R, 'value')
                          political affil
 'alphapatriot.com': 1,
                             'answerguy.blogspot.com': 0,
'beldar.blogs.com/beldarblog': 1,
                              'bensworld.patriotforum.org': 1,
'burntorangereport.com': 0,
                             'cbcbcbcb.blogspot.com': 1,
'celluloid-wisdom.com/pw': 1
'chrenkoff.blogspot.com': 1,
                              'commonsenserunswild.typepad.com': 1,
'crankyneocon.com/crankyneocon': 1,
                              'crookedtimber.org': 0,
'daisycutter.blogspot.com': 1
                              'deanesmay.com': 1,
                              decision08.blogspot.com': 1,
                              'demagogue.blogspot.com': 0,
                              'discerningtexan.blogspot.com': 1,
'dneiwert.blogspot.com': 0,
                              'ejectejecteject.com': 1,
                              elemming2.blogspot.com': 0,
                              'emergingdemocraticmajorityweblog.com/donkeyrising': 0,
                             'evangelicaloutpost.com': 1, 'gcruse.typepad.com': 1,
                              'gevkaffeegal.typepad.com/the_alliance': 1,
'hillcountryviews.blogspot.com': 1,
'homespunbloggers.blogspot.com': 1,
                              'iddybud.blogspot.com': 0,
'incite1.blogspot.com': 1,
                             'inthebullpen.com': 1,
'john.hoke.org': 0,
'jquinton.com': 1,
                              'kimdutoit.com/dr/weblog.php': 1,
'laughingwolf.net': 1,
                              'liberaloasis.com': 0,
                              'littlegreenfootballs.com/weblog': 1,
                             'mahablog.com': 0,
'mhking.mu.nu': 1,
'michellemalkin.com': 1,
                             'mudvillegazette.com': 1,
'pajamaeditors.blogspot.com': 1,
                              'papadoc.net/pinkflamingobar.html': 1,
                             papadoc.ner/pinkriamingobar.
'pardonmyenglish.com': 1,
'patriothoy.blogspot.com': 0,
'patterico.com': 1,
'politicalstrategy.org': 0,
                              'professorbainbridge.com': 1,
'reachm.com/amstreet': 0,
                              'redstate.org': 1,
'rhetoricrhythm.blogspot.com': 0,
                              'roxanne.typepad.com': 0,
                              'ruminatethis.com': 0,
                              ruminatetris.com : 0,
'sayanythingblog.com': 1,
'secureliberty.org/': 1,
'shakespearessister.blogspot.com': 0,
                              'snunes.blogspot.com': 0.
                              'talkleft.com': 0,
'the-goddess.org': 0,
'the-hamster.com': 0,
                               thespoonsexperience.com': 1,
                              'thisliberal.com': 1,
                              'timblair.net': 1,
                              'txfx.net': 1,
                             'vodkapundit.com': 1,
'washingtonmonthly.com': 0}
  In [38]: # Let's make a list of node_ids and an empty list of node colors
                          node ids = list(R.nodes)
                          node_colors = []
                         # Now, for each node, get its affiliation
for n in node_ids:
    if political_affil[n] == 0:  # 0
        node_colors.append("blue")
    elif political_affil[n] == 1:  # 1
                                                                                                                      # 0 = liberal, let's color it blue
                                                                                                                      # 1 = conservative, let's color it red
                                             node_colors.append("red")
                          # Let's inspect
                          print(node_ids[:10])
                          print(node_colors[:10])
                               ['jquinton.com', 'cbcbcbb.blogspot.com', 'timblair.net', 'mhking.mu.nu', 'demagogue.blogspot.com', 'crankyneocon.com/crankyneocon', 'homespunbloggers.blogspot.com', 'mudvill egazette.com', 'pajamaeditors.blogspot.com', 'inthebullpen.com']
['red', 'red', 'red', 'red', 'red', 'red', 'red', 'red']
```

```
In [39]: # There is a one-line alternative: # node_colors = ["blue" if political_affil[n]==0 else "red" for n in node_ids]
```



#### 3.4.2 Coloring edges by node label

Now, let's try to replicate Adamic and Glance's classic figure on our graph subset. We want to use the same intuition: make a list of edges, and then color the edges.

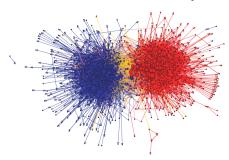
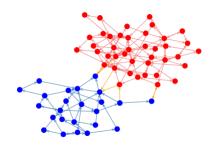


Figure 1: Community structure of political blogs (expanded set), shown using utilizing a GEM layout [11] in the GUESS[3] visualization and analysis tool. The colors reflect political orientation, red for conservative, and blue for liberal. Orange links go from liberal to conservative, and burple ones from conservative to liberal. The size of each blog reflects the number of other blogs that link to it.



Exercise: We almost replicated the graph, but not exactly. We use orange links to represent any cross-party ties, but in Adamic and Glance, the orange links only go from liberal to conservative. They use purple links to indicate the opposite direction. How would we modify the code to match their coloring scheme?

Answer: edge\_ids = list(R.edges) # Let's make a list of edge\_ids and an empty list of edge colors edge\_colors = [] for e in edge\_ids: n1,n2 = e if political\_affil[n1] == 0 and political\_affil[n2] == 0: edge\_colors.append("steelblue") # Liberal links to ibberal elif political\_affil[n1] == 1 and political\_affil[n2] == 1: edge\_colors.append("glotcoral") # Conservative links to conservative elif political\_affil[n1] == 0 and political\_affil[n2] == 1: edge\_colors.append("orange") # Liberal to conservative elif political\_affil[n1] == 1 and political\_affil[n2] == 0: edge\_colors.append("purple") # Conservative to liberal nx.draw(R, pos=pos, node\_size=100, arrowstyle="->", fontsize=7, nodelist = node\_ids, node\_color = node\_colors, edgelist = edge\_ids, # Now we just supply the edge ids edge\_color = edge\_colors # and the list of colors corresponding to them )

## 3.5 Illustrating continuous attributes

We can also use size to inform us about relevant quantities in the graph. For example, we might want to make important nodes larger, or plot the weights on edges.

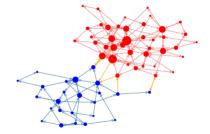
#### 3.5.1 Sizing nodes by value

Note: When sizing nodes by value, it sometimes helps to scale the value in order to draw a more dramatic contrast. We can do this by multiplying the raw value or exponentiating. You can experiment with the scaling constants until you get the appearance you want.

#### 3.5.1.1 Degree

```
In [43]: # Let's make a list of node_ids and an empty list of node sizes
node_ids = list(R.nodes)
node_sizes = []

# Add the scaled degrees for each node
for n in node_ids:
    node_sizes.append((2*R.degree(n))**1.75) # Experiment with scaling here
```



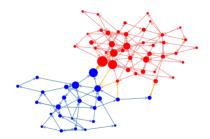
# 3.5.1.2 Pagerank

We can use the same general formula for any calculated value. For example, we can size nodes by PageRank:

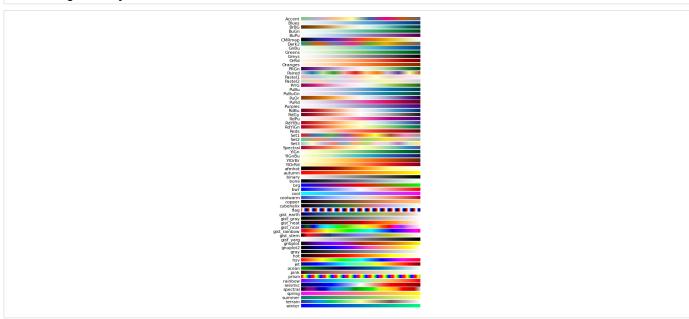
```
In [45]: # Get a dictionary of page ranks
pr = nx.pagerank(R)

# Let's make a list of node_ids and an empty list of node sizes
node_ids = list(R.nodes)
node_sizes = []

# Calculate the node sizes
for n in node_ids:
    node_sizes.append(4000*pr[n]) # Pagerank values are small (they sum to 1), so we scale aggressively
```



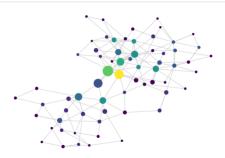
# 3.6 Coloring nodes by value



We might want to show multiple features. In that case, we can also use color as an informative dimension. Let's keep the node ids and node sizes from above, but add a color dimension that captures in-degree:

```
In [47]: # Initialize a list to store the variable associated with the color
node_color_values = []

# Add the (numeric) values to the list
for n in node_ids:
    node_color_values.append(R.in_degree(n))
```

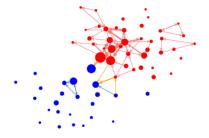


Note: We can see that in-degree does not perfectly correspond with PageRank. The nodes with the highest in degree (the lightest) are not always the ones with the highest PageRank (the biggest). PageRank depends on the weight of inbound links (and not just the number of them).

# 3.7 Sizing edges by value

Finally, we might want to use weight values to change the edges sizing. Here, let's weight a tie by how many neighbors its endpoints have in common. By now, you can probably guess how to do this:

# In [49]: # Initialize a list of edge weights edge\_weights = [] # For each edge, append a weight for n1,n2 in edge\_ids: neighbors = nx.common\_neighbors(nx.Graph(R),n1,n2) # Get common neighbors of the end points n\_neighbors = len(list(neighbors)) # Count how many of these neighbors they have in common edge\_weights.append(n\_neighbors) # Add to the list (+1, in case no common neighbors) # Plot nx.draw(R, pos=pos, node\_size=node\_sizes, arrowstyle="->", fontsize=">", fontsize=">", node\_color = node\_colors, edgelist = edge\_ids, edge\_color = edge\_colors, nodelist = node\_ids, width=edge\_weights, edge\_labels = [str(i) for i in edge\_weights] # Supply the edge weights



#### Exercise:

- Why are some edgs missing?
- How would you fix the code so that even edges with no common neighbors are drawn?

Answer: edge\_weights = [] for n1,n2 in edge\_ids: neighbors = nx.common\_neighbors(nx.Graph(R),n1,n2) # Get common neighbors of the end points n\_neighbors = len(list(neighbors)) # Count how many of these neighbors they have in common edge\_weights.append(1+n\_neighbors) # Add to the list (+1, in case no common neighbors) nx.draw(R, pos=pos, node\_size=node\_sizes, arrowstyle="->", fontsize=7, node\_color = node\_colors, edgelist = edge\_ids, edge\_color = edge\_colors, nodelist = node\_ids, width=edge\_weights, # Supply the edge weights edge\_labels = [str(i) for i in edge\_weights])

Exercise: How would you change the code so that random weights are drawn?

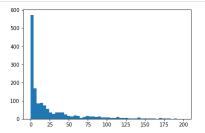
Note You can draw random numbers between zero and one using <code>random.random()</code> .

Answer: edge\_weights = [] for e in edge\_ids: edge\_weights.append(2\*random.random()) # Add a random weight nx.draw(R, pos=pos, node\_size=node\_sizes, arrowstyle="->", fontsize=7, node\_color = node\_colors, edgelist = edge\_ids, edge\_color = edge\_colors, nodelist = node\_ids, width=edge\_weights, # Supply the edge weights edge\_labels = [str(i) for i in edge\_weights])

# 3.7.1 Degree histogram

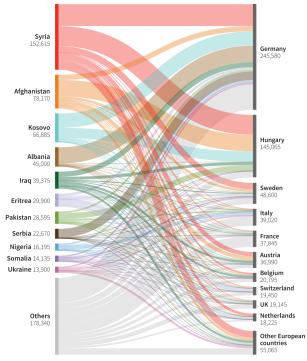
```
In [50]: # Get a list of all degrees
degrees = list(dict(P.degree()).values())

# Plot a histogram of the degree distribution
plt.hist(degrees, bins=50, range = [0,200])
plt.show()
```

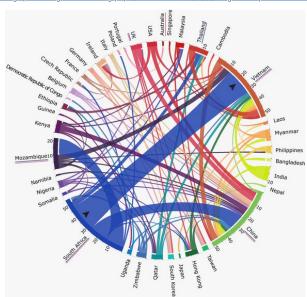


Today we have focused on simple network visualization charts, which are an easy and intuitve way to visualize and explore networks. However, it's worth noting that there are many different options.

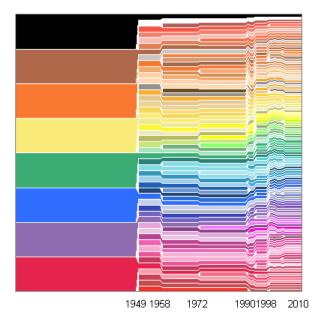
• Sankey diagrams are good for visualizing bipartite networks, such as this visualization of European asylum-seekers (http://graphics.thomsonreuters.com/15/migrants/index.html#section-asylum):



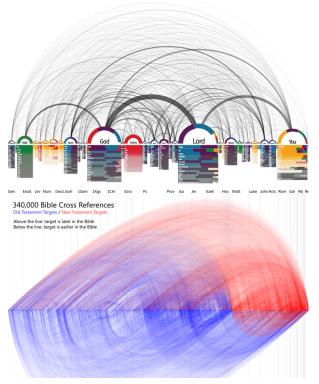
• Chord charts are helpful for visualizing flows, such as this graphic on illegal wildlife trading (https://www.wired.com/2015/06/using-news-reports-track-wildlife-black-markets/):



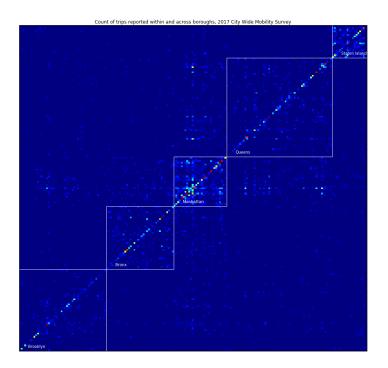
• Trees and dendrograms can be used for hierarchical data, such as this illustration of Crayola crayon color evolution in time (https://blog.revolutionanalytics.com/2010/01/crayola-crayon-colors-1949present.html):



• Arc Diagrams can help with linearly sequenced data, such as these networks of biblical and religious references (https://www.theguardian.com/news/datablog/gallery/2013/sep/05/holy-infographics-bible-visualised):



-  ${\bf Similarity\ matrices}\ {\bf can\ help\ to\ highlight\ clustering\ in\ densely\ connected\ networks:}$ 



#### More examples:

- https://python-graph-gallery.com (https://python-graph-gallery.com)
   https://flowingdata.com/category/visualization/network-visualization/ (https://flowingdata.com/category/visualization/network-visualization/)

The right visualization depends on the type of data you have, how much of it there is, and the key messages you want to highlight.