

Communities
and more

• First visualized
• Central role network
• Visualize cells beyond



Network = Graph +Data

- → connected
- — unconnected



Why networks?

A picture is worth a thousand words
simplifying complexity
Nature constitutes



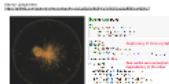
Pretty... so what?

Community detection Visualization

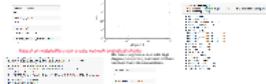
I suppose I have network data... so?

- Get data
- Figure out where the connections are
- Build a network - either manually, graph
- Think again what to do with
- Do some preliminary analysis - stats
- Visualize it
- Analyze the results

Data - Python Libraries Dependency Network



So, let's do some stats



What kind of clusters can be found based on the similarity of packages?

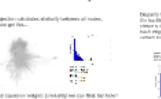
"Bipartite network"



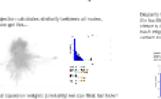
Newman Projection



Hairball :(



Backbone Filtering



Let's find communities



Small enough to visualize in Python



But still better with an other program



Communities and more

János K. Vasarhelyi
Computer Science Department, Budapest University of Technology and Economics

About me

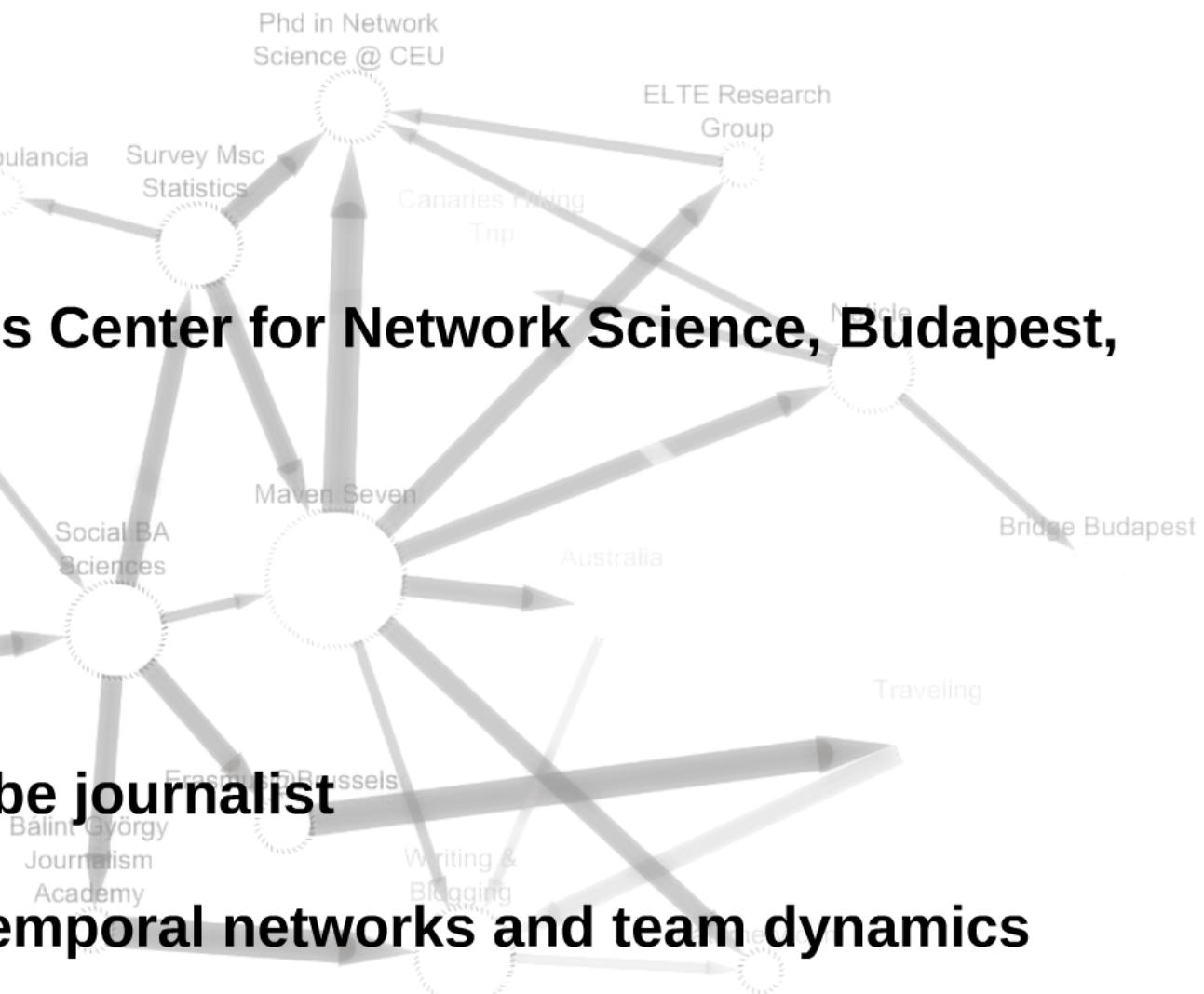
PhD student at CEU's Center for Network Science, Budapest, Hungary

Hermann Ottó
Elementary
School

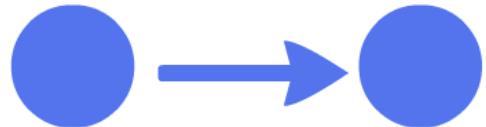
Former data analyst

Radnóti Miklós
High School

Python enthusiast



Network = Graph + Data



directed



Who follows whom on Twitter



undirected



Friendship network on Facebook

Why networks?

a picture is worth a thousand words

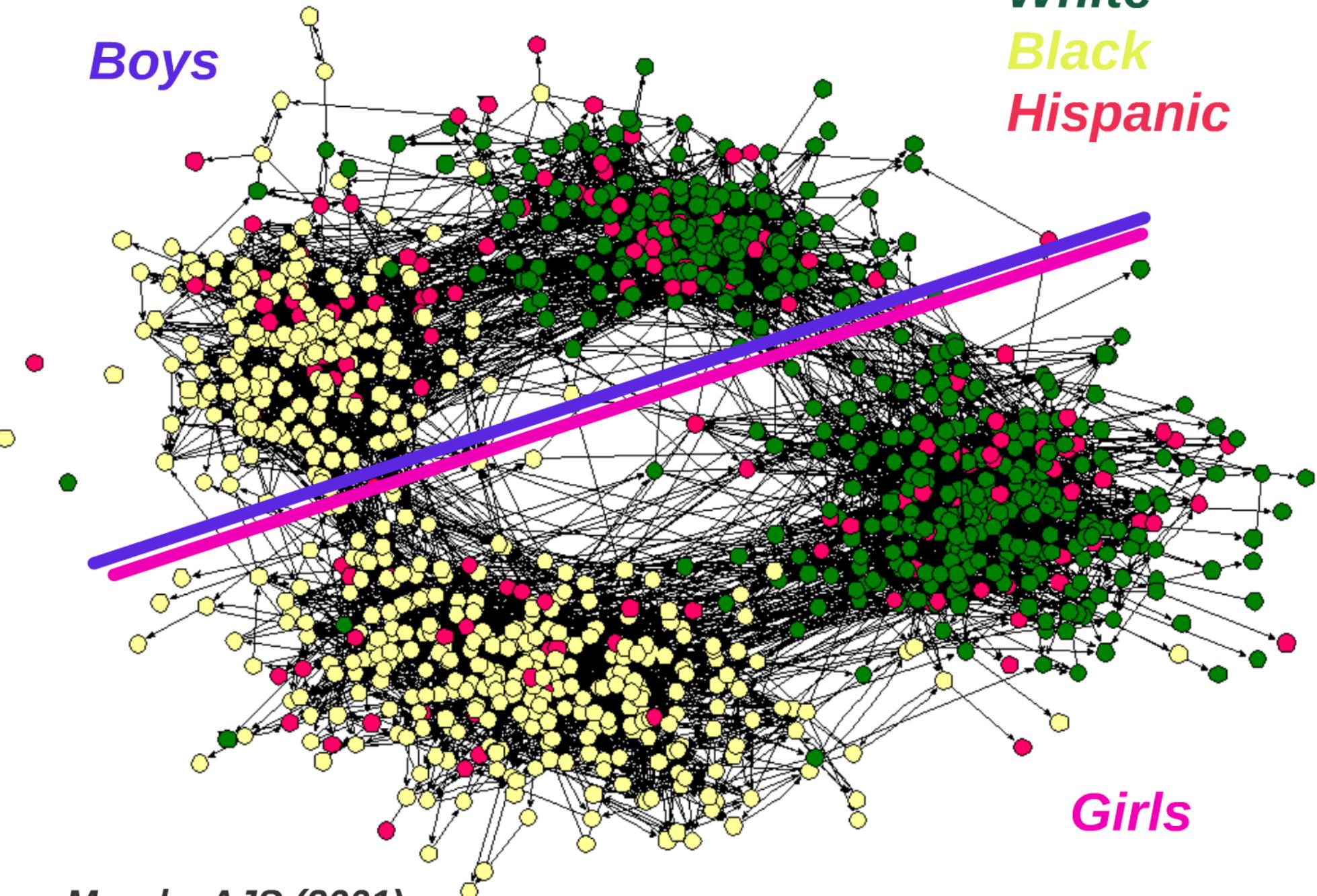
understanding complexity

hidden correlations

Boys

White
Black
Hispanic

Girls



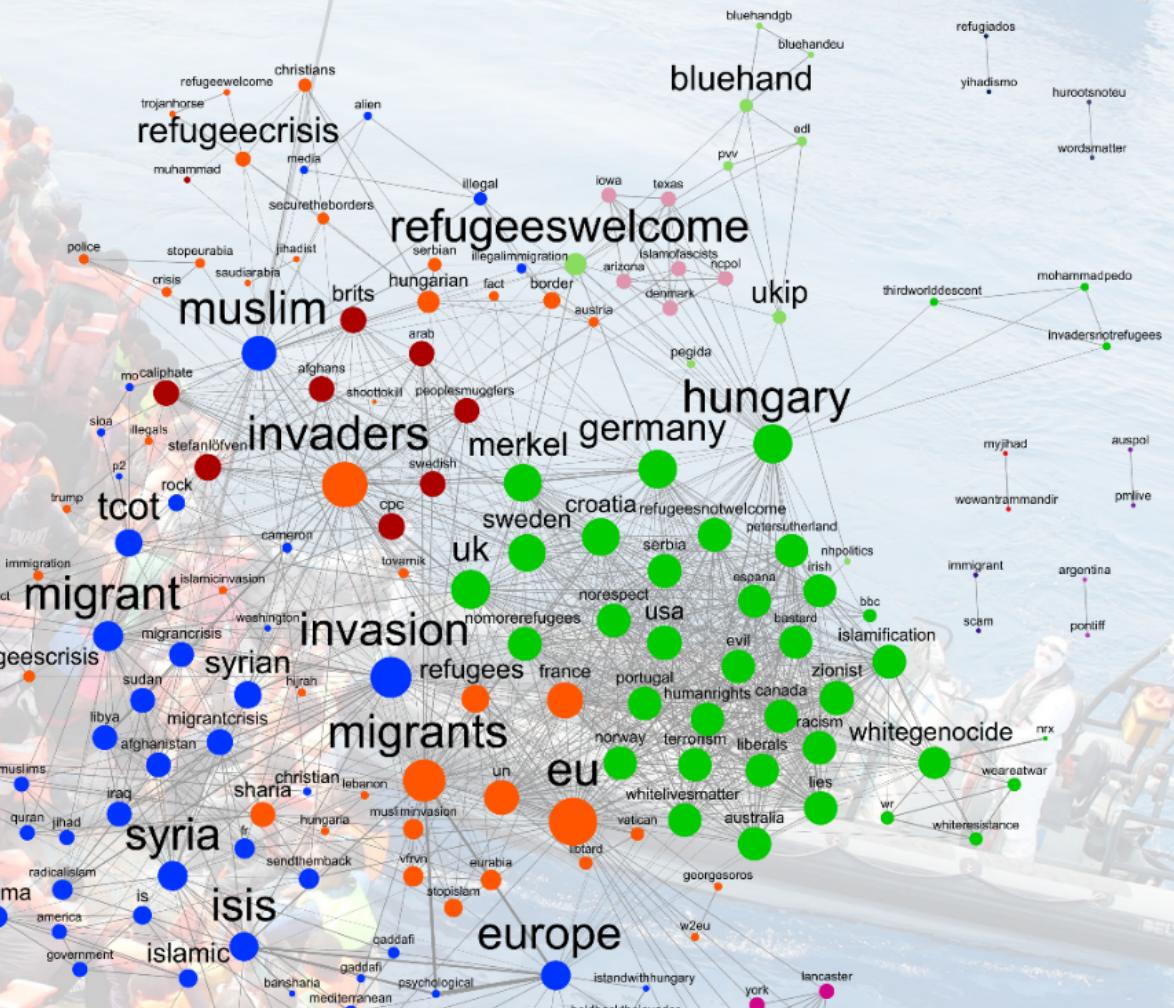
Moody, AJS (2001).

#migrantinvasion

wakeupamerica
norefugees

bbcnews

islam



Reference:

#Migrant invasion' as a Trojan horseshoe - The influx of conspiracy theories on European refugee crisis on Social Media In: P. Krekó, Cs. Molnár, A. Félix, I. Barna, M. Boneva: Trust within Europe, Political Capital. Budapest, 2015.

Pretty... so what?

Community detection

built-in function:

Communities

K-Clique

`k_clique_communities (G, k[, cliques])`

Find k-clique communities in graph using the percolation method.

<http://perso.crans.org/aynaud/communities/>

<http://igraph.org/python/doc/igraph.Graph-class.html>

Visualization

<http://matplotlib.org/>

<http://pygraphviz.github.io/>

<https://github.com/erocarrera/pydot>

<http://lightning-viz.org/>

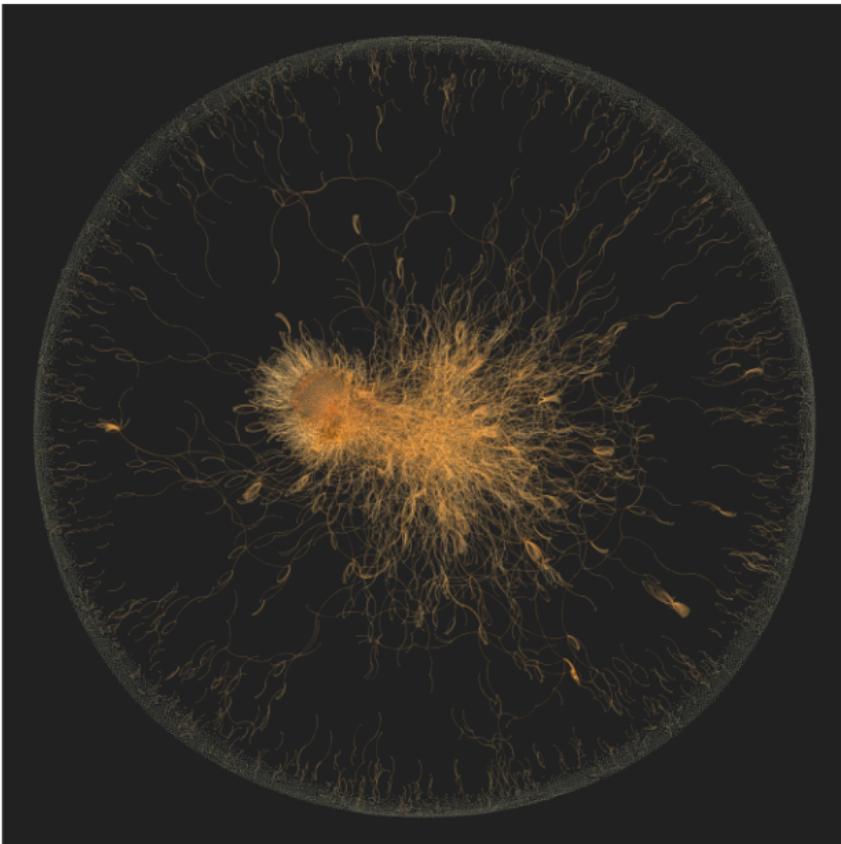
I suppose I have network data... so?

- Get data
- Figure out where the connections are
- Build up the network --- networkx, igraph
- Think again what is ur aim
- Do some preliminary analysis -- stats
- Visualize (if u can)
- Analyze the results

Data - Python Libraries Dependency Network

Source: @ogirardot

<https://github.com/ogirardot/meta-deps/tree/a61d2c0ef8d246c3e666f2a191df303ea416da7>



```
import networkx as nx, json
from base64 import b64decode

data = []
with open('pypi-deps.csv', 'r') as file:
    for line in file:
        name, version, deps = line.split('\t')
        deps = json.loads(b64decode(deps))
        data+= [(name, version, deps)]
```

```
G=nx.Graph()
edges_dict={}
for ex in data:
    name, version, deps = ex
    G.add_node("%s-%s" % (name, version))
    for dep in deps:
        if not '#' in dep: G.add_edge("%s-%s" % (name, version), dep.replace("\", ""))

nx.write_edgelist(G,'Edges')
```

Super easy to have a graph

```
G.edges()[:10]
[("u'', 'simplemail-0.3'),
(u'requests>=0.13', 'pathod-0.3.0'),
('zope.component-4.0.2', 'u'zope.interface>=3.8.0'),
('zope.component-4.0.2', 'u'zope.event'),
('zope.component-4.0.2', 'u'setuptools'),
(u'Products.CMFDynamicViewFTI', 'Products.CMFPlone-4.1.1'),
(u'Products.CMFDynamicViewFTI', 'Products.CMFPlone-4.1.3'),
(u'Products.CMFDynamicViewFTI', 'Products.CMFPlone-4.1.2'),
(u'Products.CMFDynamicViewFTI', 'Products.CMFPlone-4.1.4'),
(u'Products.CMFDynamicViewFTI', 'plone.app.layout-2.2.2')]
```

Two nodes are connected if one is the dependency of the other

So, let's do some stats

```
G.number_of_nodes()
```

```
20693
```

```
G.number_of_edges()
```

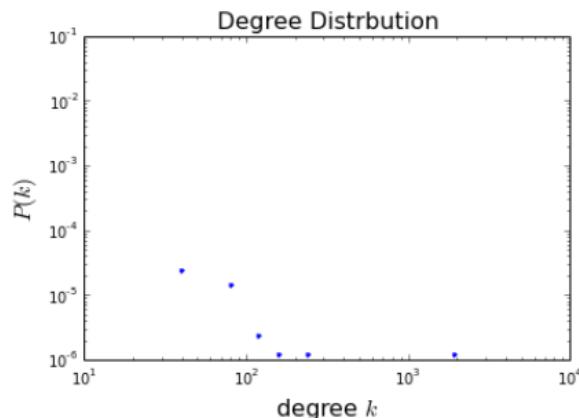
```
14071
```

```
nx.density(G)
```

```
6.572476337473712e-05
```

```
nx.number_connected_components(G)
```

```
11776
```



Based on matplotlib u can create network analytical charts

We have very few nodes with high degree (*setuptools*), but most of them has less than 100 connections.

```
: degrees['pandas']
```

```
: 5
```

```
: nx.neighbors(G, 'pandas')
```

```
: ['django-openbudget-0.1.0',
'django-openportfolio-0.1.0',
'PyUvVis-0.1.1-2',
'zipline-0.5.6',
'bamboo-data-0.5.2.3']
```

```
: degrees=nx.degree(G)
sorted_degree = sorted(degrees.items(), key=operator.itemgetter(1))
sorted_degree[-20::]
```

```
: [(u'ZODB3', 71),
(u'argparse', 72),
(u'zope.i18nmessageid', 76),
(u'zope.publisher', 79),
(u'fanstatic', 92),
(u'Flask', 98),
('Products.CMFPlone-4.1.2', 100),
('Products.CMFPlone-4.1.1', 100),
('Products.CMFPlone-4.1.3', 100),
('Products.CMFPlone-4.1.4', 100),
(u'zope.schema', 102),
(u'distribute', 106),
(u'zc.buildout', 107),
(u'xml', 108),
(u'django', 115),
(u'simplejson', 133),
(u'requests', 143),
(u'zope.component', 190),
(u'zope.interface', 239),
(u'setuptools', 1931)]
```

```
def make_a_plot(deg_list, title1, title2, title3, n):
bin_edges = np.logspace(np.log10(min(deg_list)), np.log10(max(deg_list)), num=n)
density, _ = np.histogram(deg_list, bins=bin_edges, density=True)

bin_edges_lin = np.linspace(min(deg_list), max(deg_list))
density_lin, _ = np.histogram(deg_list, bins=bin_edges_lin, density=True)

fig = plt.figure(figsize=(6,4))
plt.loglog(bin_edges_lin[:-1], density_lin, marker='.', linestyle='none', color='b')
plt.loglog(bin_edges[:-1], density, marker='o', linestyle='none', color='r', markeredgecolor='0.6')

plt.xlabel(title1, fontsize=16)
plt.ylabel(title2, fontsize=16)
plt.title(title3, fontsize=16)
plt.show()
```

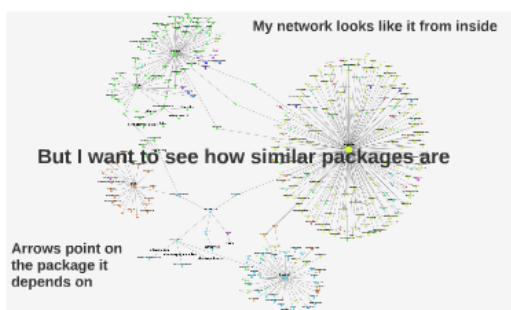
In the similarity of packages?

- Think again what is ur aim
 - Do some preliminary analysis -- stats
 - Visualize (if u can)
 - Analyze the results

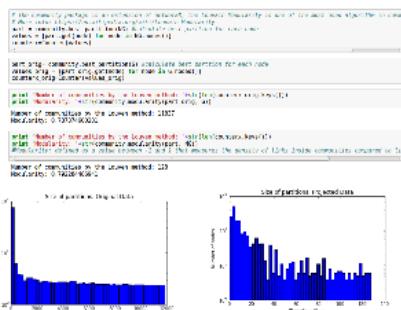


What kind of clusters can be found based on the similarity of packages?

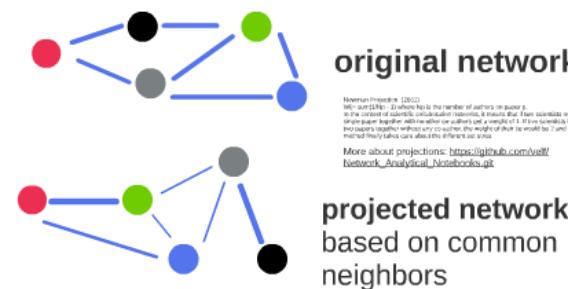
"Bipartite network"



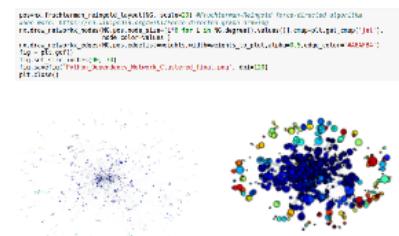
Let's find communities



Newman Projection

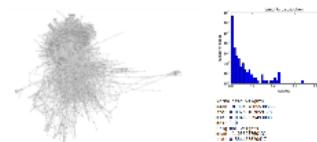


Small enough to visualize
in Python



Hairball :(

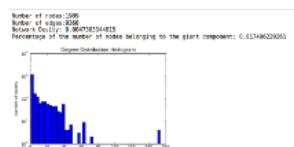
Projection calculates similarity between all nodes
so we get this...



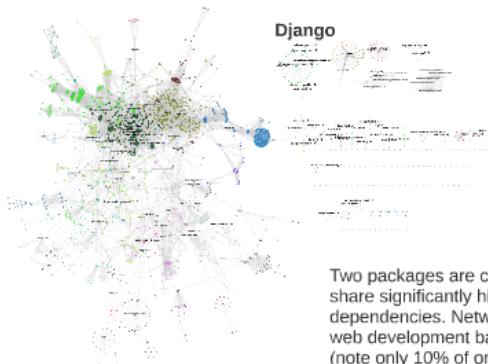
But based on weights (similarity) we can filter, but how?

Backbone Filtering

Disparity filter is a network reduction algorithm to extract the backbone structure of undirected weighted network . I create a threshold based on the Bonferroni Correction for each edge and decide is it significantly important for the certain node or not.



But still better with an other program



Two packages are connected if they share significantly high level of dependencies. Network kept mainly web development based packages (note only 10% of original data in it).

[View Document](#)



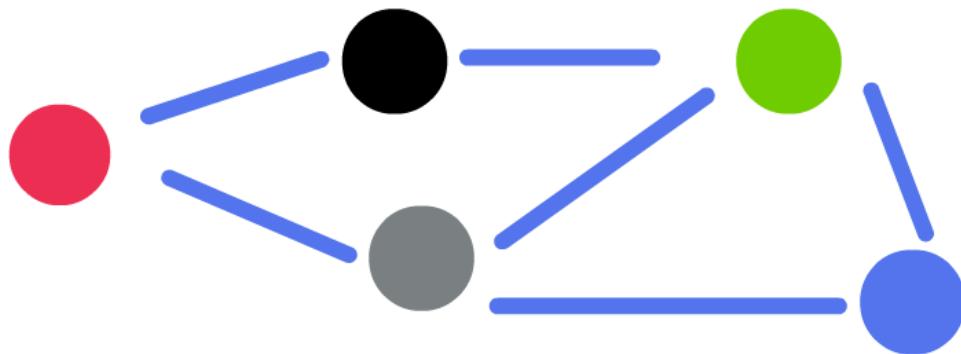
"Bipartite network"

My network looks like it from inside

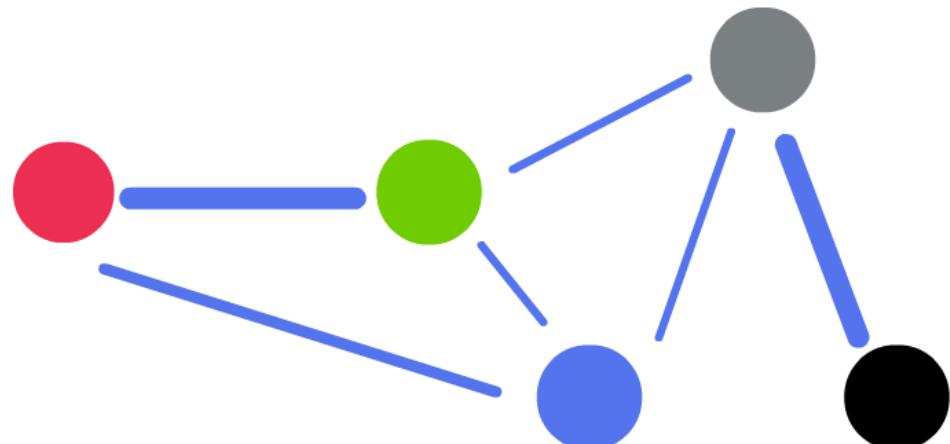
But I want to see how similar packages are

Arrows point on
the package it
depends on

Newman Projection



original network



projected network
based on common
neighbors

Newman Projection (2001)

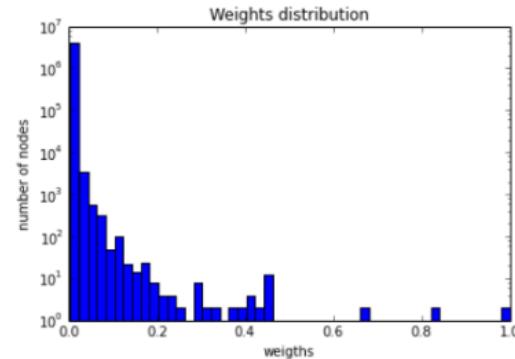
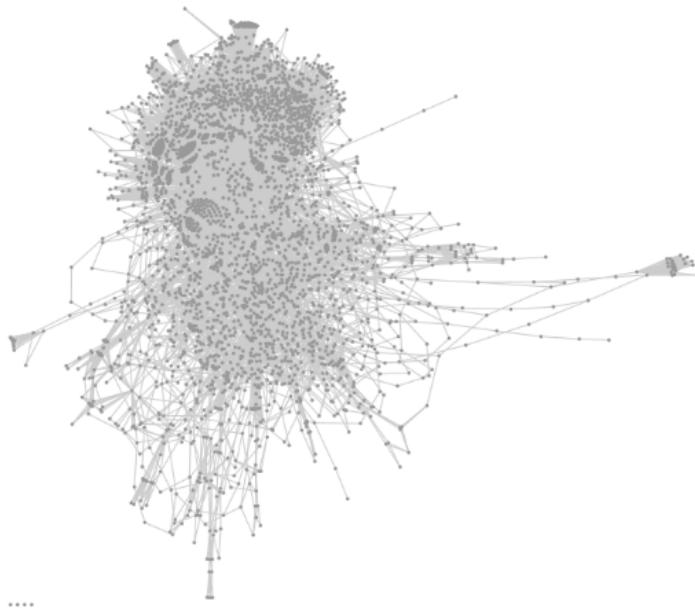
$W_{ij} = \sum(1/N_p - 1)$ where N_p is the number of authors on paper p.

In the context of scientific collaboration networks, it means that if two scientists only wrote a single paper together with no other co-authors get a weight of 1. If two scientists have written two papers together without any co-author, the weight of their tie would be 2 and so on. This method finally takes care about the different set sizes.

More about projections: [https://github.com/velf/
Network_Analytical_Notebooks.git](https://github.com/velf/Network_Analytical_Notebooks.git)

Hairball :(

Projection calculates similarity between all nodes,
so we get this...



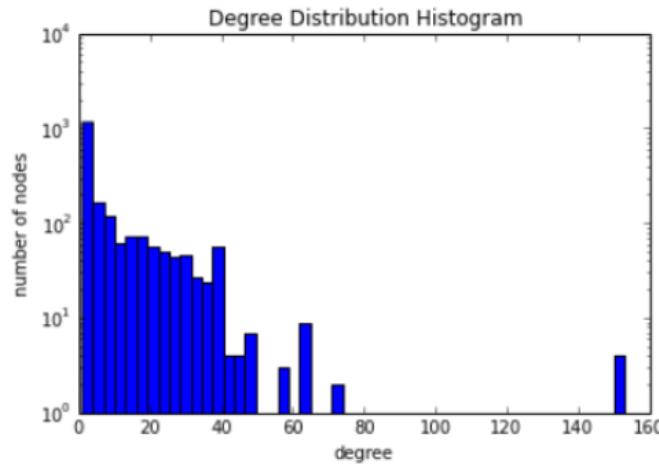
Normalized weights
mean: 0.00487685530556
std: 0.00260107659178
min: 0.00460829493088
max: 1.0
Original weights
mean: 1.05827760131
std: 0.564433620417
min: 1
max: 217

But based on weights (similarity) we can filter, but how?

Backbone Filtering

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```
Number of nodes:1989
Number of edges:9368
Network Desity: 0.0047383344815
Percentage of the number of nodes belonging to the giant component: 0.817496229261
```



Let's find communities

```
# The community package is an extension of networkX, the Louvain Modularity is one of the most used algorithm in commu  
# More info: https://en.wikipedia.org/wiki/Louvain_Modularity  
part = community.best_partition(NG) #calculate best partition for each node  
values = [part.get(node) for node in NG.nodes()]  
counterx=Counter(values)
```

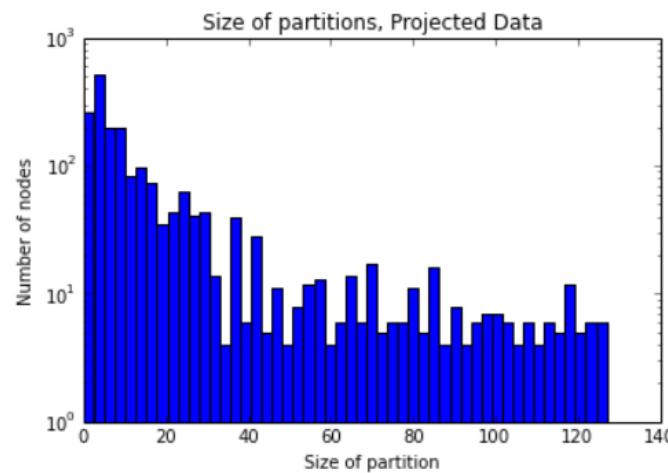
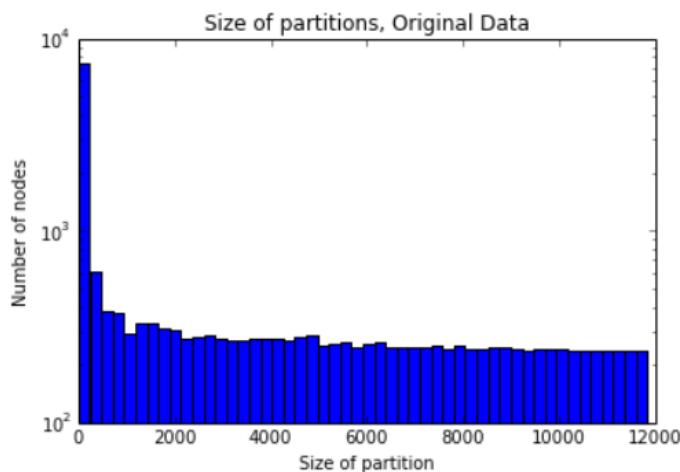
```
part_orig= community.best_partition(G) #calculate best partition for each node  
values_orig = [part_orig.get(node) for node in G.nodes()]  
counterx_orig=Counter(values_orig)
```

```
print 'Number of communities by the Louven method: '+str(len(counterx.keys()))  
print 'Modularity: '+str(community.modularity(part, G))
```

```
Number of communities by the Louven method: 11837  
Modularity: 0.787374600201
```

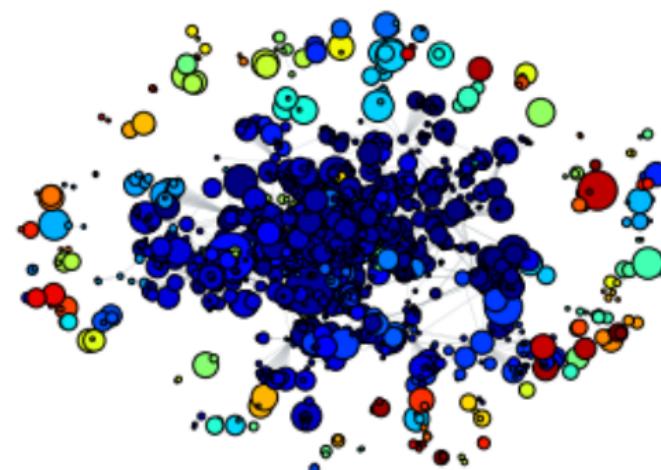
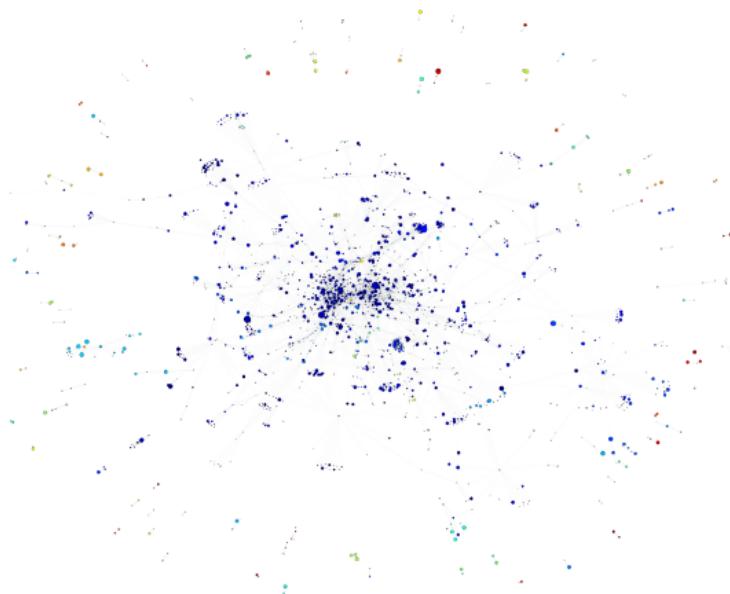
```
print 'Number of communities by the Louven method: '+str(len(counterx.keys()))  
print 'Modularity: '+str(community.modularity(part, NG))  
#Modularity: defined as a value between -1 and 1 that measures the density of links inside communities compared to lin
```

```
Number of communities by the Louven method: 128  
Modularity: 0.792284486941
```

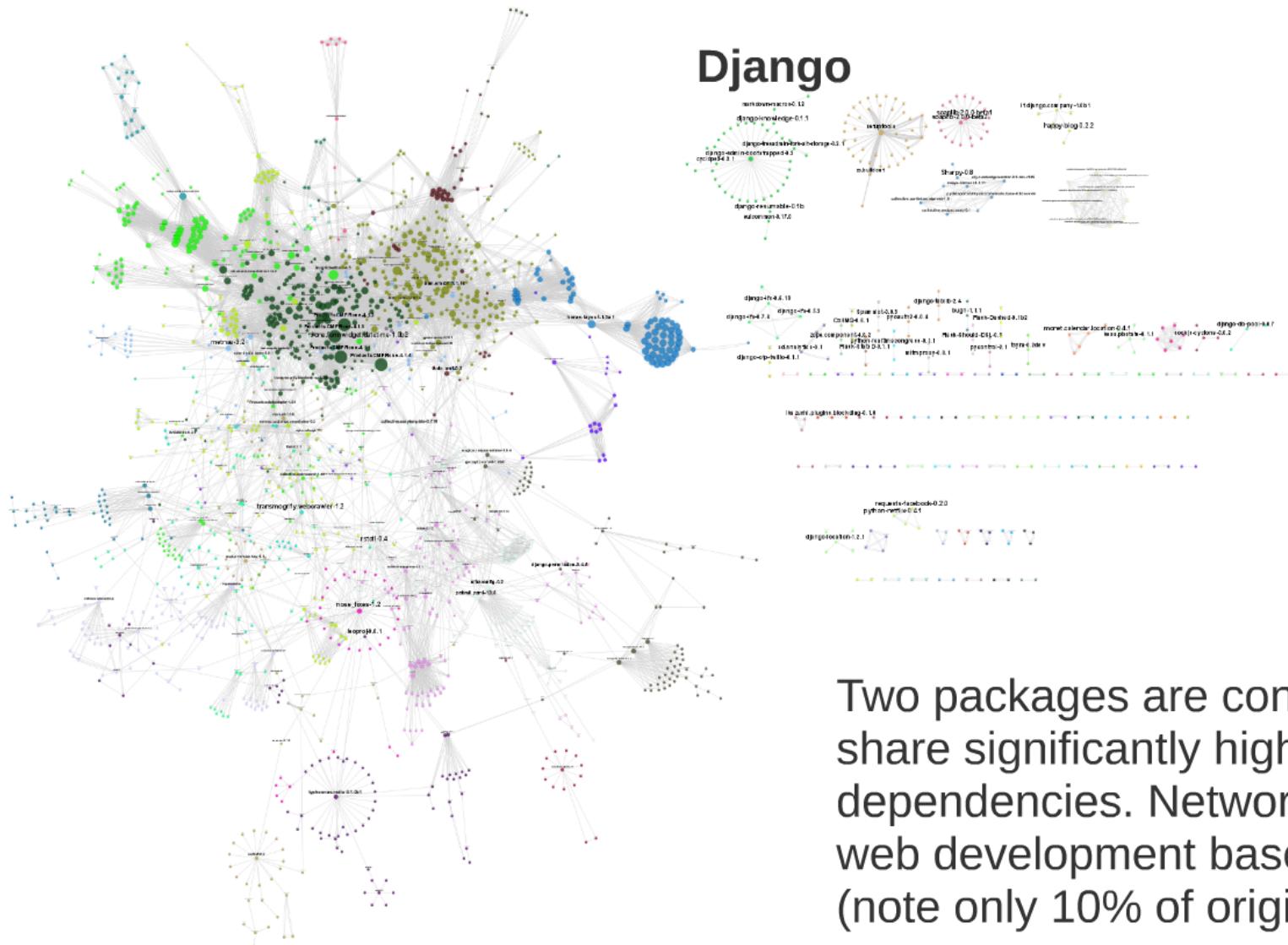


Small enough to visualize in Python

```
pos=nx.fruchterman_reingold_layout(NG, scale=20) #Fruchterman-Reingold force-directed algorithm
#See more: https://en.wikipedia.org/wiki/Force-directed\_graph\_drawing
nx.draw_networkx_nodes(NG,pos,node_size=[i*6 for i in NG.degree().values()],cmap=plt.get_cmap('jet'),
                      node_color=values )
nx.draw_networkx_edges(NG,pos,edgelist=weights,width=weights_to_plot,alpha=0.5,edge_color='#A6AFB4')
fig = plt.gcf()
fig.set_size_inches(90, 70)
fig.savefig('Python_Dependency_Network_Clustered_final.png', dpi=120)
plt.close()
```

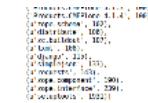


But still better with an other program



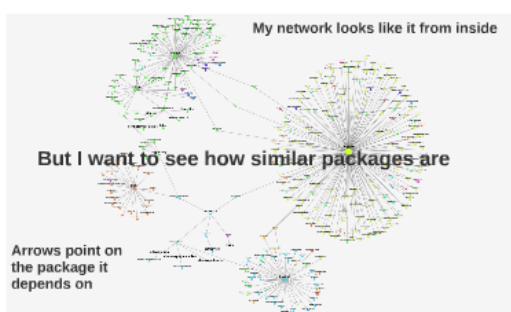
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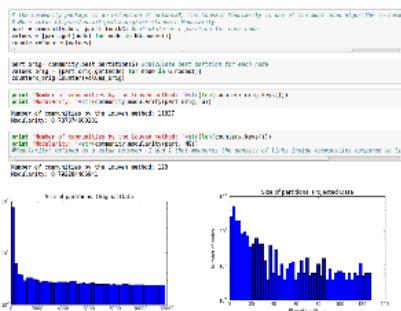


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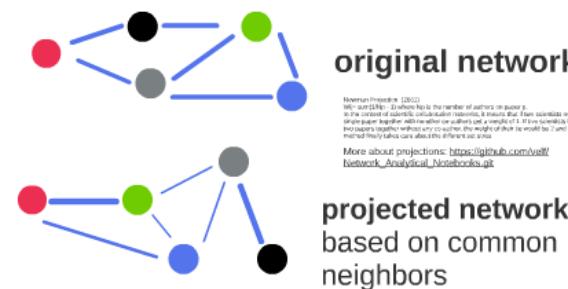
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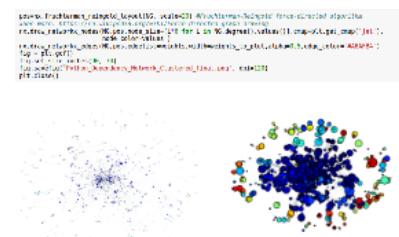
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Newman Projection

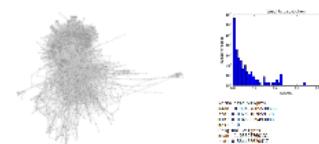


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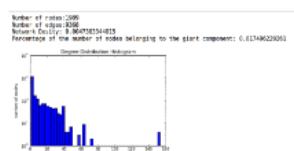
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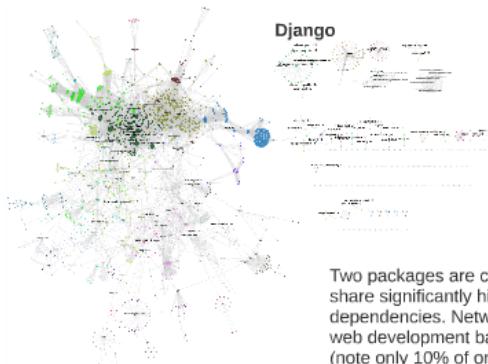
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A screenshot of a web-based application titled "Little Extra for the Web". The main title is "Little Extra for the Web". Below it, a sub-section titled "Interactive pages with lightning" is shown. A large, bold, red text box contains the message "U can zoom in and play with it!". Below this, there is a toolbar with icons for "File", "Edit", "View", "Insert", "Format", "Tools", and "Help". A status bar at the bottom shows the URL "http://www.littleextra.com/littleextra.html" and the text "Page 1 of 1, 100% zoomed".

LITTLE EXTRA FOR THE WEB

Interactive graphs wth Lightning

```
import os
from lightning import Lightning
from numpy import random, asarray, linspace, corrcoef
from colorsys import hsv_to_rgb
from sklearn import datasets
```

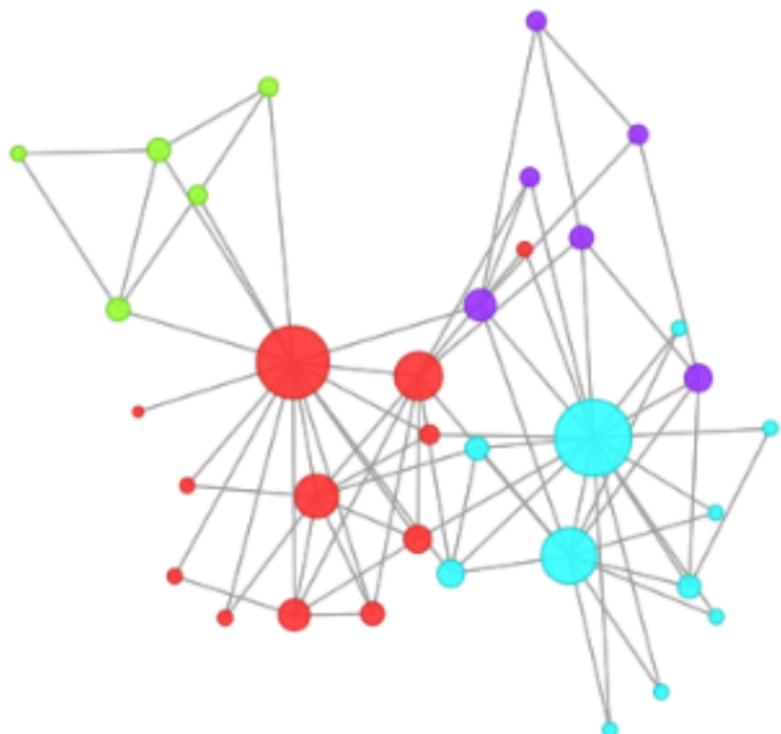
U can zoom in and play with it!

```
lgn = Lightning(ipython=True, host='http://public.lightning-viz.org')
```

⚡ Lightning initialized

Connected to server at <http://public.lightning-viz.org>

```
mat = nx.adjacency_matrix(G).todense()
n=G.number_of_nodes()
c = [list(asarray(hsv_to_rgb(float(y)/4, 0.8, 1.0))*255) for x,y in part.iteritems()]
g = G.degree().values()
lgn.force(mat, color=c, size=(asarray(g) + 1.5))
```



Summary

NetworkX is a good tool, with huge support from the scientific community

Still lack of the newest results/methods of network science (Come and work on it!)

Not efficient in every case (large and very dense networks, visualization)

Think twice if u want network visualizations (not always worth the effort)

Other good python packages (iGraph, written in C/C++ -faster, but not the best documentation)

For visualization: Gephi, Cytoscape



Thx for ur attention:)

Orsi Vasarhelyi
CEU, Center for Network Science