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SMA LAB ASSIGNMENT-2

(Use the networkx package to find the different types of centralities for any network)

Importing the necessary packages

In [1]:
```
import networkx as nx
import numpy as np
```

In [2]:
```
from IPython.display import SVG
from sknetwork.visualization import svg_graph
from sknetwork.data import Bunch
from sknetwork.ranking import PageRank
```

In [3]:
```
def draw_graph(G, show_names=False, node_size=1, font_size=10, edge_width=0.5)

    adjacency = nx.to_scipy_sparse_matrix(G, nodelist=None, dtype=None, weight

    names = np.array(list(G.nodes()))

    graph = Bunch()
    graph.adjacency = adjacency
    graph.names = np.array(names)

    pagerank = PageRank()

    scores = pagerank.fit_transform(adjacency)

    if show_names:

        image = svg_graph(graph.adjacency, font_size=font_size, node_size=node

    else:

        image = svg_graph(graph.adjacency, node_size=node_size, width=700, hei

    return SVG(image)
```

Krackhardt kite graph

The Krackhardt kite is the simple graph on 10 nodes and 18 edges.

In [4]:
```
G = nx.krackhardt_kite_graph()
df = nx.to_pandas_edgelist(G)[['source', 'target']] # cut the weights, for vis
G = nx.from_pandas_edgelist(df)
```

In [5]:
```
nx.krackhardt_kite_graph
```

Out[5]:
```
<function networkx.generators.small.krackhardt_kite_graph(create_using=None)>
```

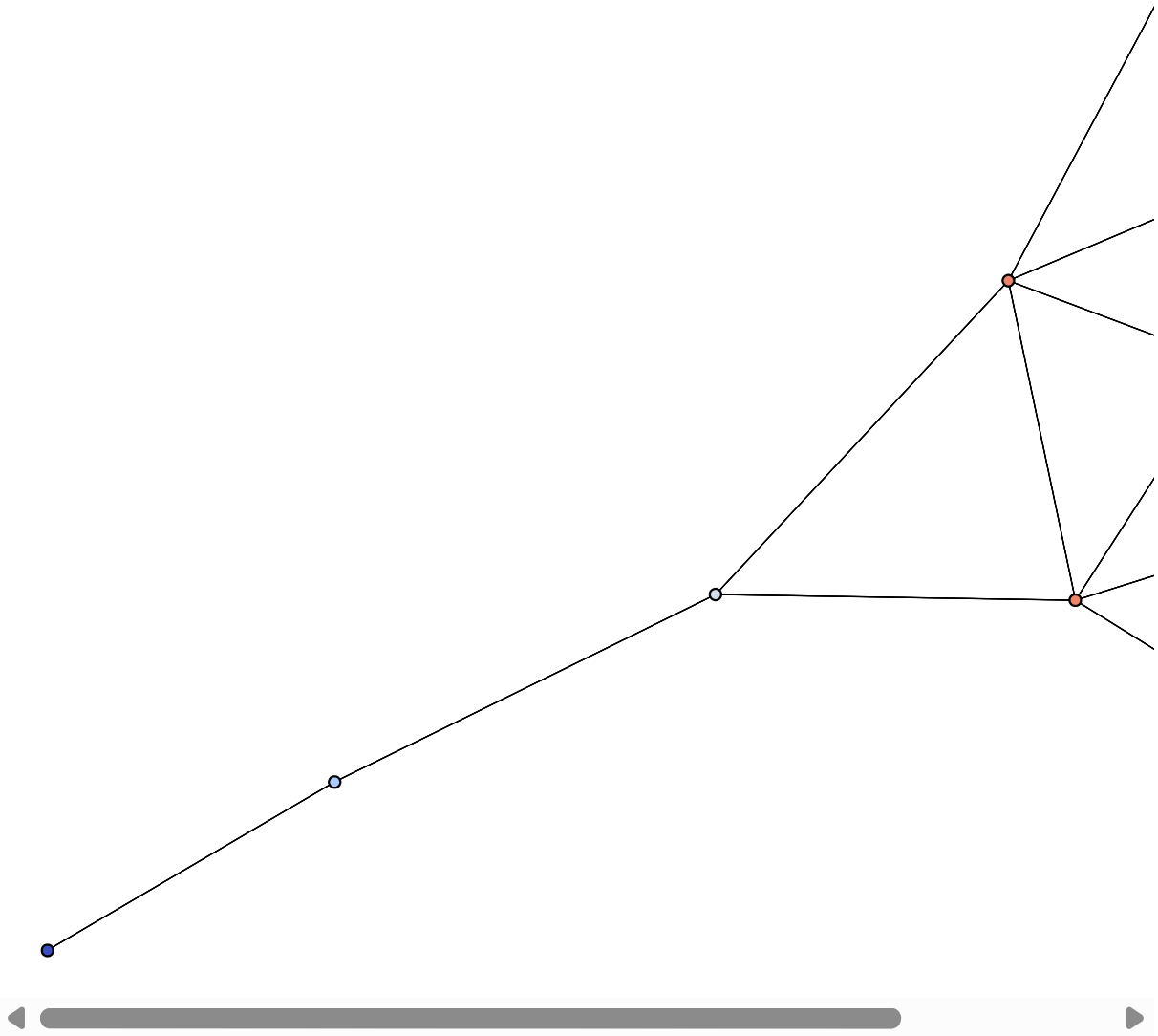
In [6]:
```
# this is a network / graph

draw_graph(G, node_size=3)
```

```
C:\Users\visit\AppData\Local\Temp\ipykernel_13792\1794451103.py:3: Deprecatio
nWarning:

The scipy.sparse array containers will be used instead of matrices
in Networkx 3.0. Use `to_scipy_sparse_array` instead.
  adjacency = nx.to_scipy_sparse_matrix(G, nodelist=None, dtype=None, weight
='weight', format='csr')
```

Out[6]:



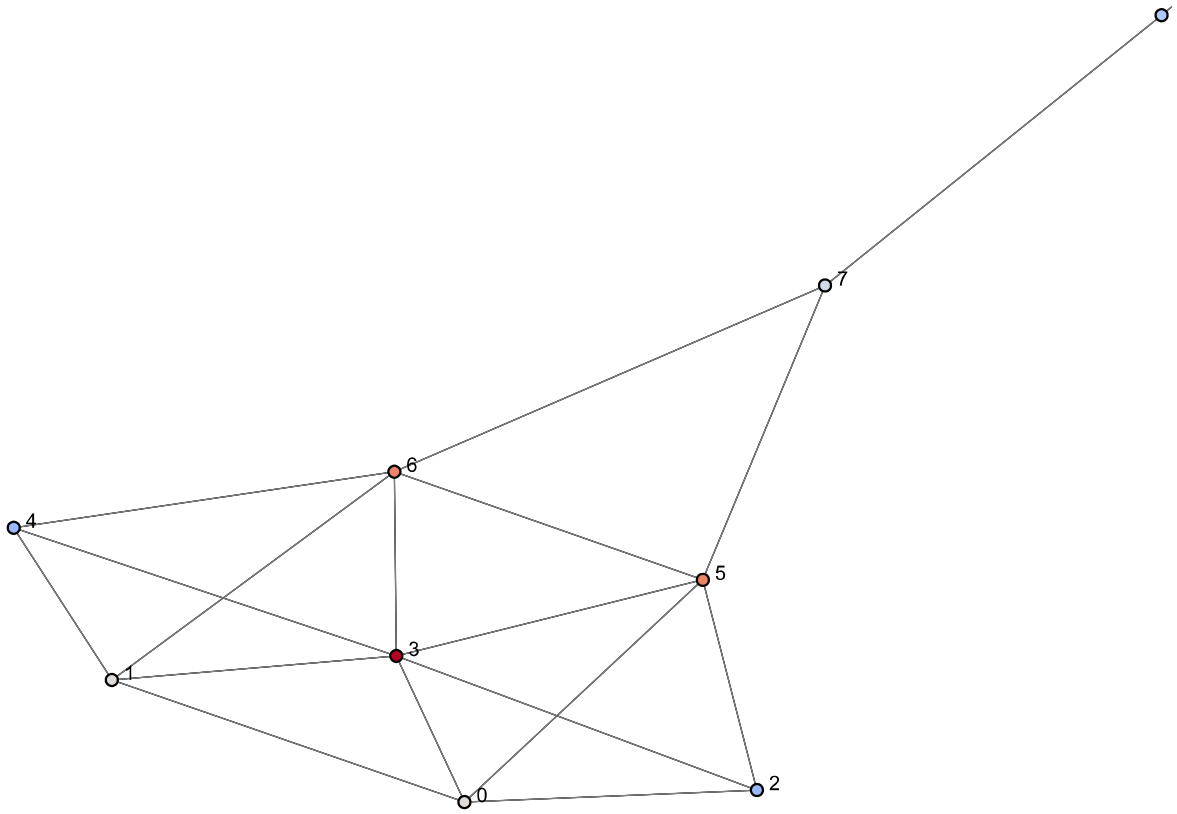
In [7]:
```
# with labels

draw_graph(G, node_size=3, show_names=True)
```

```
C:\Users\visit\AppData\Local\Temp\ipykernel_13792\1794451103.py:3: Deprecatio
nWarning:

The scipy.sparse array containers will be used instead of matrices
in Networkx 3.0. Use `to_scipy_sparse_array` instead.
  adjacency = nx.to_scipy_sparse_matrix(G, nodelist=None, dtype=None, weight
='weight', format='csr')
```

Out[7]:



In [8]:
```
# these are ten of the nodes

sorted(G.nodes)[0:10]
```

Out[8]: `[0, 1, 2, 3, 4, 5, 6, 7, 8, 9]`

1.Degree Centrality

Degree Centrality: Importance based on the number of degrees (edges)

In [9]:
```
import pandas as pd
```

In [10]:
```
deg_cent = nx.degree_centrality(G)
```

In [11]:
```
deg_cent_df = pd.DataFrame().from_dict(deg_cent, orient='index')
deg_cent_df.columns = ['degree_centrality']
deg_cent_df.sort_values('degree_centrality', ascending=False, inplace=True)
```

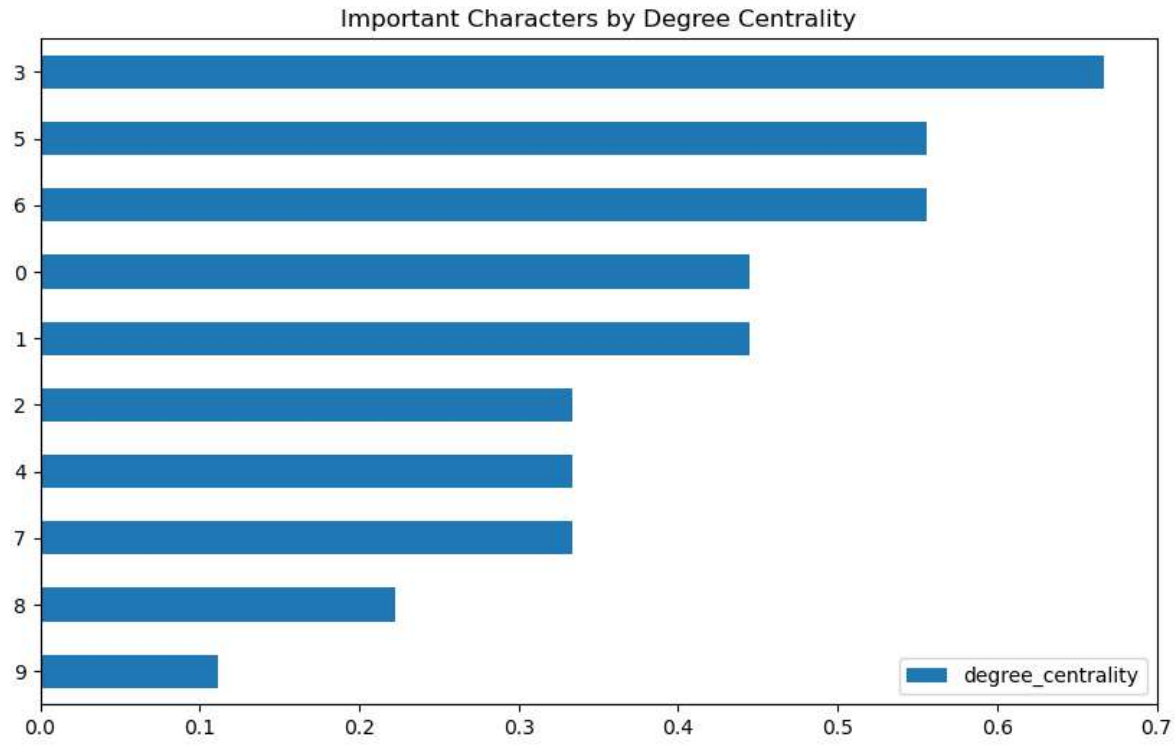
In [12]:
```
deg_cent_df.head(10)
```

Out[12]:

	degree_centrality
3	0.666667
5	0.555556
6	0.555556
0	0.444444
1	0.444444
2	0.333333
4	0.333333
7	0.333333
8	0.222222
9	0.111111

In [13]:
```
title = 'Important Characters by Degree Centrality'

deg_cent_df.head(10).plot.barh(figsize=(10,6), title=title).invert_yaxis()
```



2.Betweenness Centrality

Betweenness Centrality: Importance based on whether a node sits between other nodes; Information flows through them. Can also be gatekeepers. They have power.

In [14]:
```
betw_cent = nx.betweenness_centrality(G)
```

In [15]:
```
betw_cent_df = pd.DataFrame().from_dict(betw_cent, orient='index')
betw_cent_df.columns = ['betweenness_centrality']
betw_cent_df.sort_values('betweenness_centrality', ascending=False, inplace=Tr
```

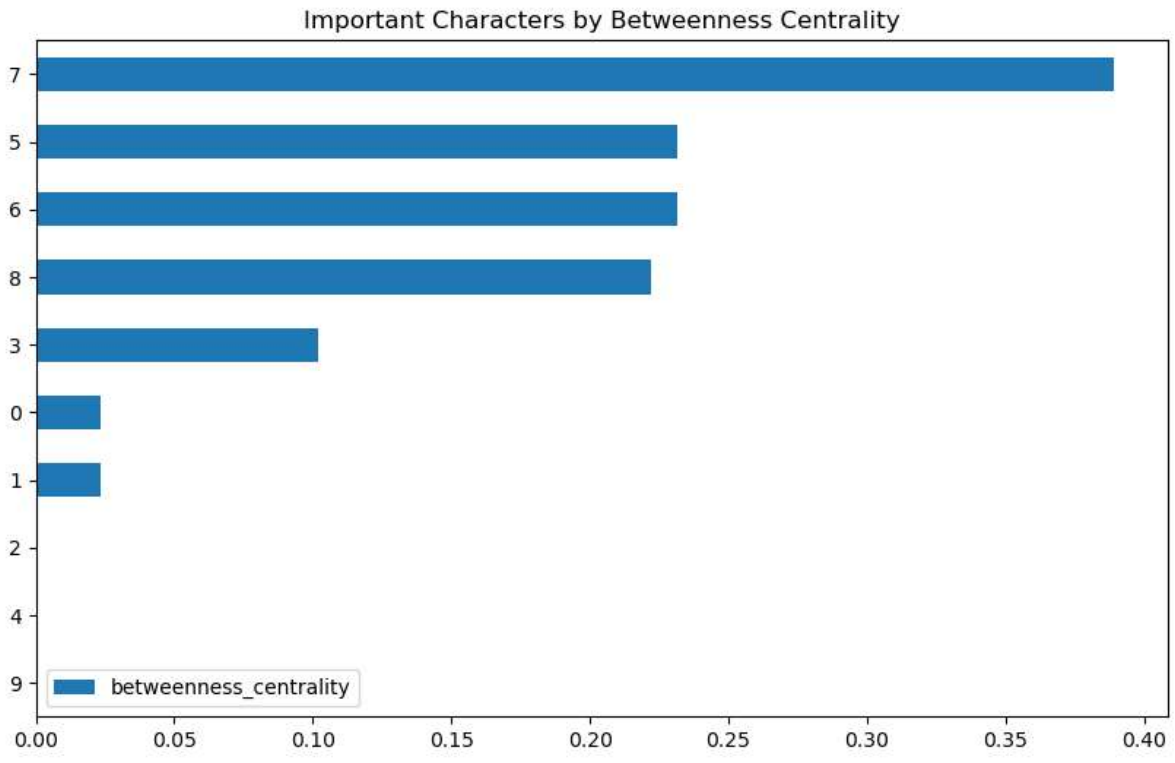
In [16]:
```
betw_cent_df.head(10)
```

Out[16]:

	betweenness_centrality
7	0.388889
5	0.231481
6	0.231481
8	0.222222
3	0.101852
0	0.023148
1	0.023148
2	0.000000
4	0.000000
9	0.000000

In [17]:
```
title = 'Important Characters by Betweenness Centrality'

betw_cent_df.head(10).plot.barh(figsize=(10,6), title=title).invert_yaxis()
```



3.Closeness Centrality

Closeness Centrality: Importance based on a nodes closeness to other nodes. Has to do with number of steps away.

In [18]:
```
close_cent = nx.closeness_centrality(G)
```

In [19]:
```
close_cent_df = pd.DataFrame().from_dict(close_cent, orient='index')
close_cent_df.columns = ['closeness_centrality']
close_cent_df.sort_values('closeness_centrality', ascending=False, inplace=Tru
```

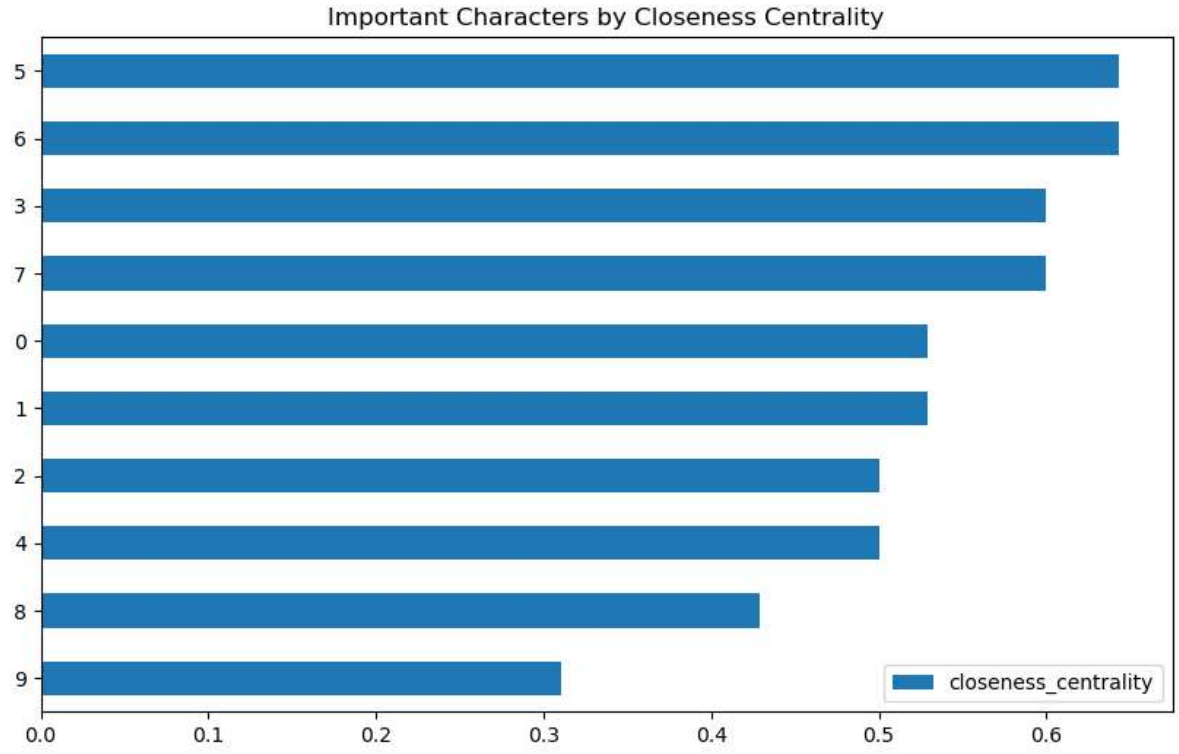
In [20]:
```
close_cent_df.head(10)
```

Out[20]:

	closeness_centrality
5	0.642857
6	0.642857
3	0.600000
7	0.600000
0	0.529412
1	0.529412
2	0.500000
4	0.500000
8	0.428571
9	0.310345

In [21]:
```
title = 'Important Characters by Closeness Centrality'

close_cent_df.head(10).plot.barh(figsize=(10,6), title=title).invert_yaxis()
```



4.PageRank

PageRank : Importance based on number of inbound and outbound edges. Inbound is more important than outbound.

In [22]:
```
page_rank = nx.pagerank(G)
```

In [23]:
```
pr_df = pd.DataFrame().from_dict(page_rank, orient='index')
pr_df.columns = ['page_rank']
pr_df.sort_values('page_rank', ascending=False, inplace=True)
```

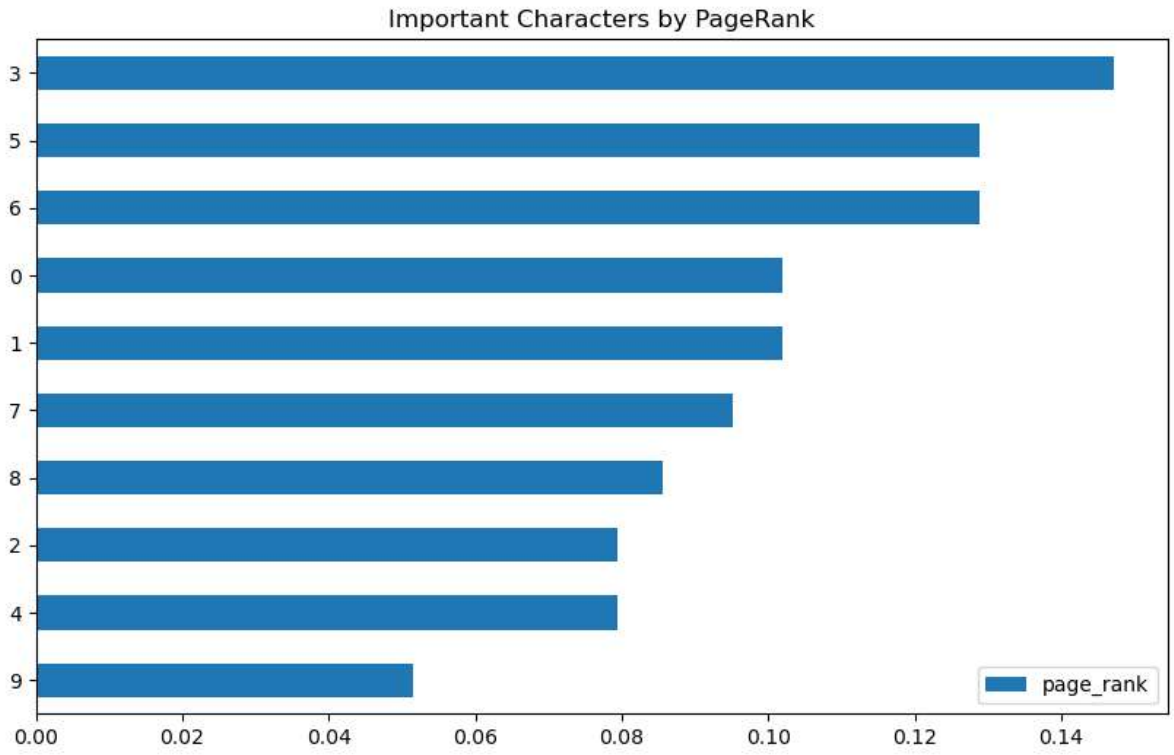
In [24]:
```
pr_df.head(10)
```

Out[24]:

	page_rank
3	0.147148
5	0.128907
6	0.128907
0	0.101920
1	0.101920
7	0.095248
8	0.085696
2	0.079418
4	0.079418
9	0.051420

In [25]:
```
title = 'Important Characters by PageRank'

pr_df.head(10).plot.barh(figsize=(10,6), title=title).invert_yaxis()
```



Tutte Graph

It is a graph with 46 vertices and 69 edges. It is important because it is an exception to Tait's conjecture which states that every 3-regular polyhedron has a Hamiltonian cycle.

In [26]:
```
G = nx.tutte_graph()
```

In [27]:
```
df = nx.to_pandas_edgelist(G)[['source', 'target']] # cut the weights, for vis
G = nx.from_pandas_edgelist(df)
```

1. Degre Centality

In [28]:
```
deg_cent = nx.degree_centrality(G)
```

In [29]:
```
deg_cent_df = pd.DataFrame().from_dict(deg_cent, orient='index')
deg_cent_df.columns = ['degree_centrality']
deg_cent_df.sort_values('degree_centrality', ascending=False, inplace=True)
```

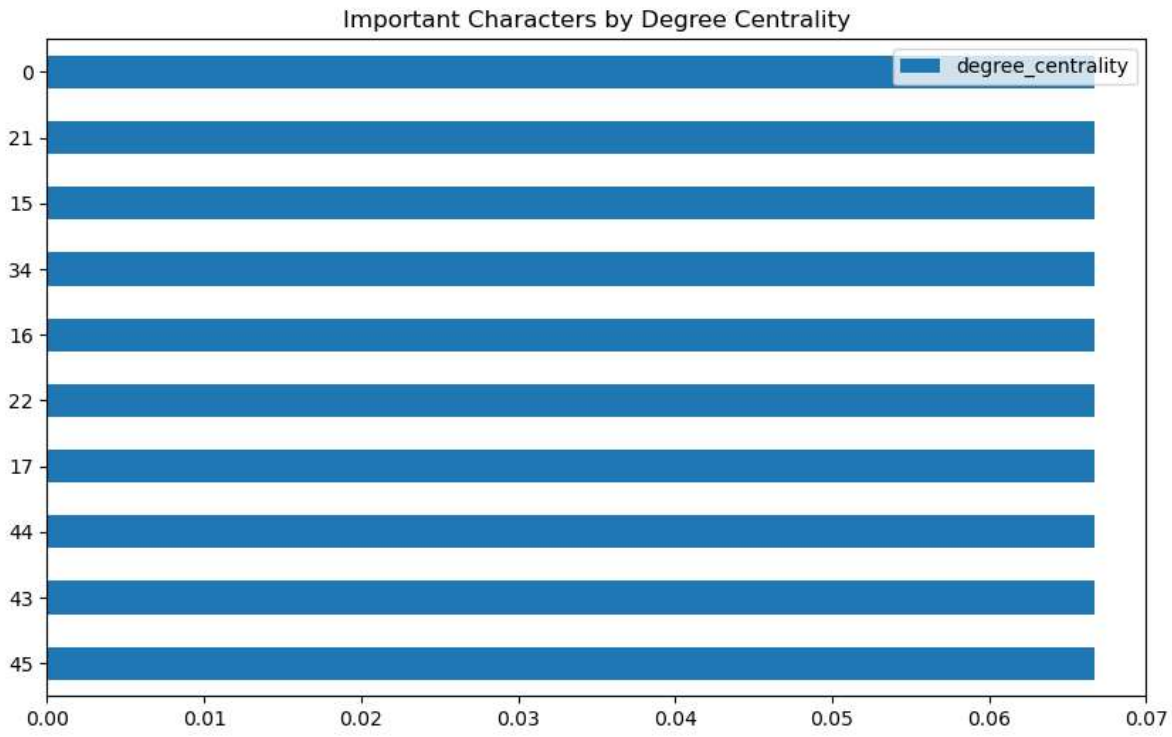
In [30]:
```
deg_cent_df.head(10)
```

Out[30]:

	degree_centrality
0	0.066667
21	0.066667
15	0.066667
34	0.066667
16	0.066667
22	0.066667
17	0.066667
44	0.066667
43	0.066667
45	0.066667

In [31]:
```
title = 'Important Characters by Degree Centrality'

deg_cent_df.head(10).plot.barh(figsize=(10,6), title=title).invert_yaxis()
```



2. Between Centrality

In [32]:
```
betw_cent = nx.betweenness_centrality(G)
```

In [33]:
```
betw_cent_df = pd.DataFrame().from_dict(betw_cent, orient='index')
betw_cent_df.columns = ['betweenness_centrality']
betw_cent_df.sort_values('betweenness_centrality', ascending=False, inplace=Tr
```

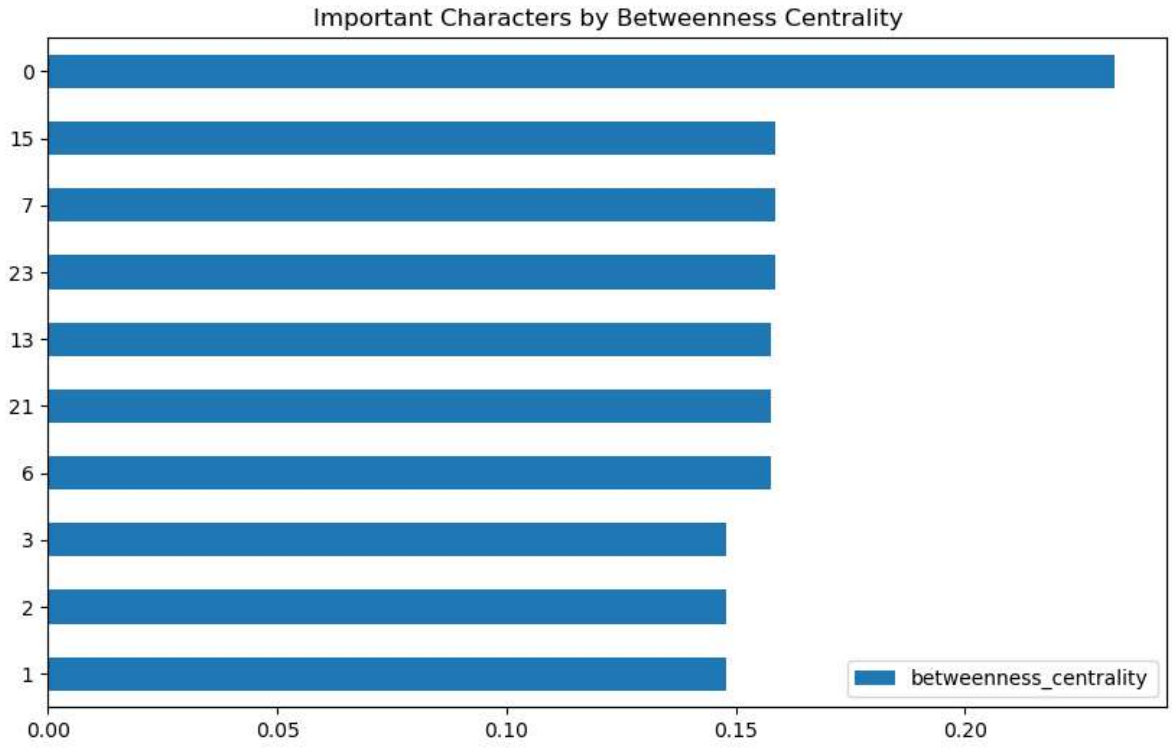
In [34]:
```
betw_cent_df.head(10)
```

Out[34]:

	betweenness_centrality
0	0.232540
15	0.158514
7	0.158514
23	0.158514
13	0.157588
21	0.157588
6	0.157588
3	0.148040
2	0.148040
1	0.148040

In [35]:
```
title = 'Important Characters by Betweenness Centrality'

betw_cent_df.head(10).plot.barh(figsize=(10,6), title=title).invert_yaxis()
```



3. Closeness Cnetrality

In [36]:
```
close_cent = nx.closeness_centrality(G)
```

In [37]:
```
close_cent_df = pd.DataFrame().from_dict(close_cent, orient='index')
close_cent_df.columns = ['closeness_centrality']
close_cent_df.sort_values('closeness_centrality', ascending=False, inplace=Tru
```

In [38]:
```
close_cent_df.head(10)
```

Out[38]:

	closeness_centrality
0	0.277778
6	0.263158
21	0.263158
13	0.263158
15	0.258621
23	0.258621
7	0.258621
14	0.257143
2	0.257143
22	0.257143

In [39]:
```
df = nx.to_pandas_edgelist(G)[['source', 'target']] # cut the weights, for vis
G = nx.from_pandas_edgelist(df)
```

4. PageRank

In [40]:
```
page_rank = nx.pagerank(G)
```

In [41]:
```
pr_df = pd.DataFrame().from_dict(page_rank, orient='index')
pr_df.columns = ['page_rank']
pr_df.sort_values('page_rank', ascending=False, inplace=True)
```

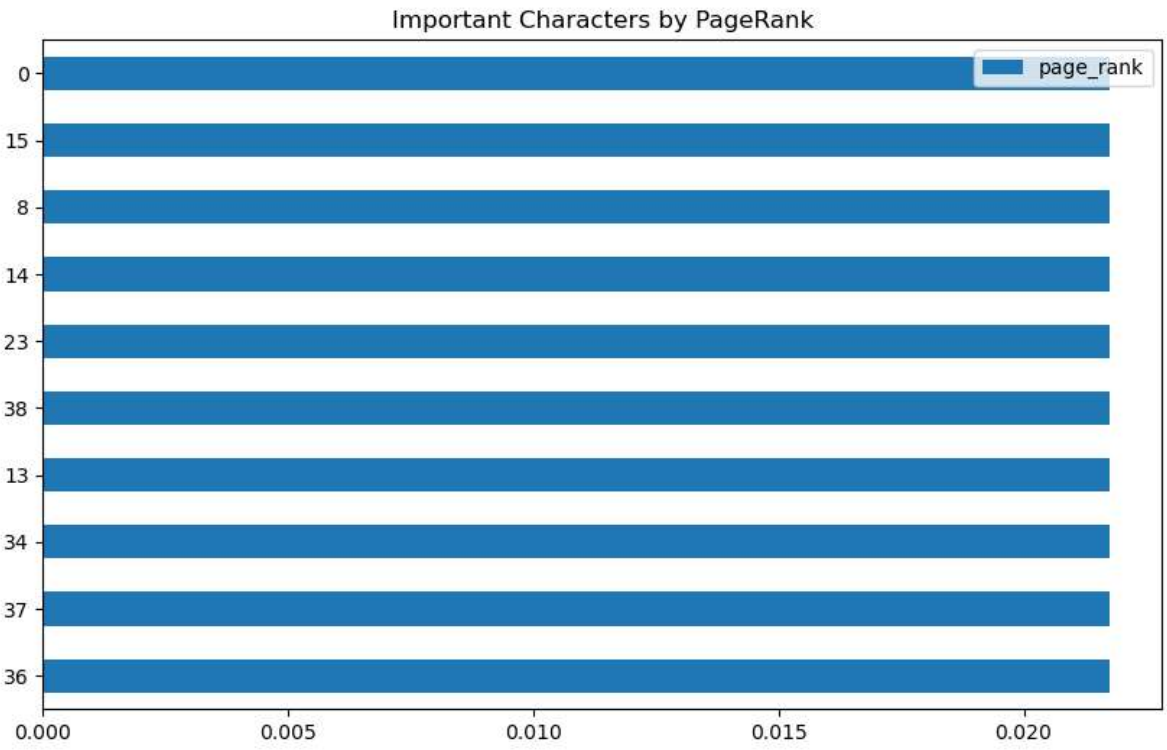
In [42]:
```
pr_df.head(10)
```

Out[42]:

	page_rank
0	0.021739
15	0.021739
8	0.021739
14	0.021739
23	0.021739
38	0.021739
13	0.021739
34	0.021739
37	0.021739
36	0.021739

In [43]:
```
title = 'Important Characters by PageRank'

pr_df.head(10).plot.barh(figsize=(10,6), title=title).invert_yaxis()
```



In [ ]:
```

```