

Network Analysis of Facebook Large Dataset

```
# Step 1: Install and Import Required Libraries
```

```
import pandas as pd
import networkx as nx
import matplotlib.pyplot as plt
import seaborn as sns
from networkx.algorithms.community import greedy_modularity_communities
```

```
# Step 2: Load the Dataset
```

```
# Update file path if using Google Colab
edges_df = pd.read_csv('musae_facebook_edges.csv')
large_df = pd.read_csv('facebook_large.csv')
G = nx.from_pandas_edgelist(edges_df, source='id_1', target='id_2')
```

```
# Load node attributes (pages types)
```

```
node_attributes = large_df.set_index('id')[['page_name', 'page_type']].to_dict('index')
nx.set_node_attributes(G, node_attributes)
```

```
# Display the first five rows
```

```
edges_df.head(), large_df.head()
```

```
↗ (   id_1  id_2
0      0  18427
1      1  21708
2      1  22208
3      1  22171
4      1   6829,
      id      facebook_id      page_name \
0      0  145,647,315,578,475      The Voice of China 中国好声音
1      1      191,483,281,412      U.S. Consulate General Mumbai
2      2  144,761,358,898,518      ESET
3      3  568,700,043,198,473  Consulate General of Switzerland in Montreal
4      4  1,408,935,539,376,130      Mark Bailey MP - Labor for Miller

      page_type
0      tvshow
1  government
2      company
3  government
4  politician )
```

```
# Check for missing values
```

```
print("Missing values:\n", edges_df.isnull().sum())
print("Missing values in large :\n", large_df.isnull().sum())
```

```
↗ Missing values:
   id_1    0
id_2    0
dtype: int64
Missing values in large :
   id    0
```

```

facebook_id      0
page_name        0
page_type        0
dtype: int64

```

```

# Network Statistics
num_nodes = G.number_of_nodes()
num_edges = G.number_of_edges()
avg_degree = sum(dict(G.degree()).values()) / num_nodes
density = nx.density(G)
largest_component = max(nx.connected_components(G), key=len)
largest_component_size = len(largest_component)
clustering_coefficient = nx.average_clustering(G)

stats = {
    'Total Nodes': num_nodes,
    'Total Edges': num_edges,
    'Average Degree': avg_degree,
    'Network Density': density,
    'Largest Component Size': largest_component_size,
    'Average Clustering Coefficient': clustering_coefficient
}
stats

```

```

➡ {'Total Nodes': 22470,
   'Total Edges': 171002,
   'Average Degree': 15.220471740097908,
   'Network Density': 0.000677398715568023,
   'Largest Component Size': 22470,
   'Average Clustering Coefficient': 0.3597383824426942}

```

```

degree_centrality = nx.degree_centrality(G)
betweenness_centrality = nx.betweenness_centrality(G, k=100)
eigenvector_centrality = nx.eigenvector_centrality(G, max_iter=500)

top_betweenness = sorted(betweenness_centrality.items(), key=lambda x: x[1], reverse=True)
top_eigenvector = sorted(eigenvector_centrality.items(), key=lambda x: x[1], reverse=True)

{'Top Betweenness Centrality': top_betweenness, 'Top Eigenvector Centrality': top_eigenvector}

```

```

➡ {'Top Betweenness Centrality': [(701, 0.11949092720334413),
                                   (11003, 0.0820581799375244),
                                   (19743, 0.03644124599614159),
                                   (21729, 0.034025507902130166),
                                   (11158, 0.02838733743030904),
                                   (21120, 0.02569192931234774),
                                   (8482, 0.02318501394216652),
                                   (22171, 0.02269551474760911),
                                   (5049, 0.022119006725882046),
                                   (17983, 0.021191140733387306)],
   'Top Eigenvector Centrality': [(16895, 0.17781707337310618),
                                   (14497, 0.16061001208256728),
                                   (1387, 0.13635222410071537),
                                   (2442, 0.12104428239701732),
                                   (8139, 0.12083968693763034),
                                   (11003, 0.0820581799375244),
                                   (19743, 0.03644124599614159),
                                   (21729, 0.034025507902130166),
                                   (11158, 0.02838733743030904),
                                   (21120, 0.02569192931234774),
                                   (8482, 0.02318501394216652),
                                   (22171, 0.02269551474760911),
                                   (5049, 0.022119006725882046),
                                   (17983, 0.021191140733387306)]}

```

```
(19743, 0.11706026233850285),
(21729, 0.11584286287283624),
(4502, 0.11376368244597415),
(15236, 0.10815449185206008),
(9220, 0.10642511189041222)]}]
```

```
import matplotlib.pyplot as plt
import seaborn as sns
from collections import Counter
```

```
# Function to plot degree distribution
def plot_degree_distribution(G):
    degree_sequence = sorted([d for n, d in G.degree()], reverse=True)
    plt.figure(figsize=(10, 6))
    plt.hist(degree_sequence, bins=50, log=True, edgecolor="black")
    plt.xlabel("Degree (Number of Connections)")
    plt.ylabel("Frequency (Log Scale)")
    plt.title("Degree Distribution of Facebook Pages Network")
    plt.grid(True)
    plt.show()
```

```
# Function to plot network structure (for a sample to reduce complexity)
def plot_network_structure(G, title="Network Visualization", sample_size=500):
    sampled_nodes = list(dict(G.degree()).keys())[:sample_size] # Take a subset of nodes
    subgraph = G.subgraph(sampled_nodes)

    plt.figure(figsize=(10, 8))
    pos = nx.spring_layout(subgraph, seed=42)
    nx.draw_networkx_nodes(subgraph, pos, node_size=10, node_color="blue", alpha=0.7)
    nx.draw_networkx_edges(subgraph, pos, alpha=0.3)
    plt.title(title)
    plt.show()
```

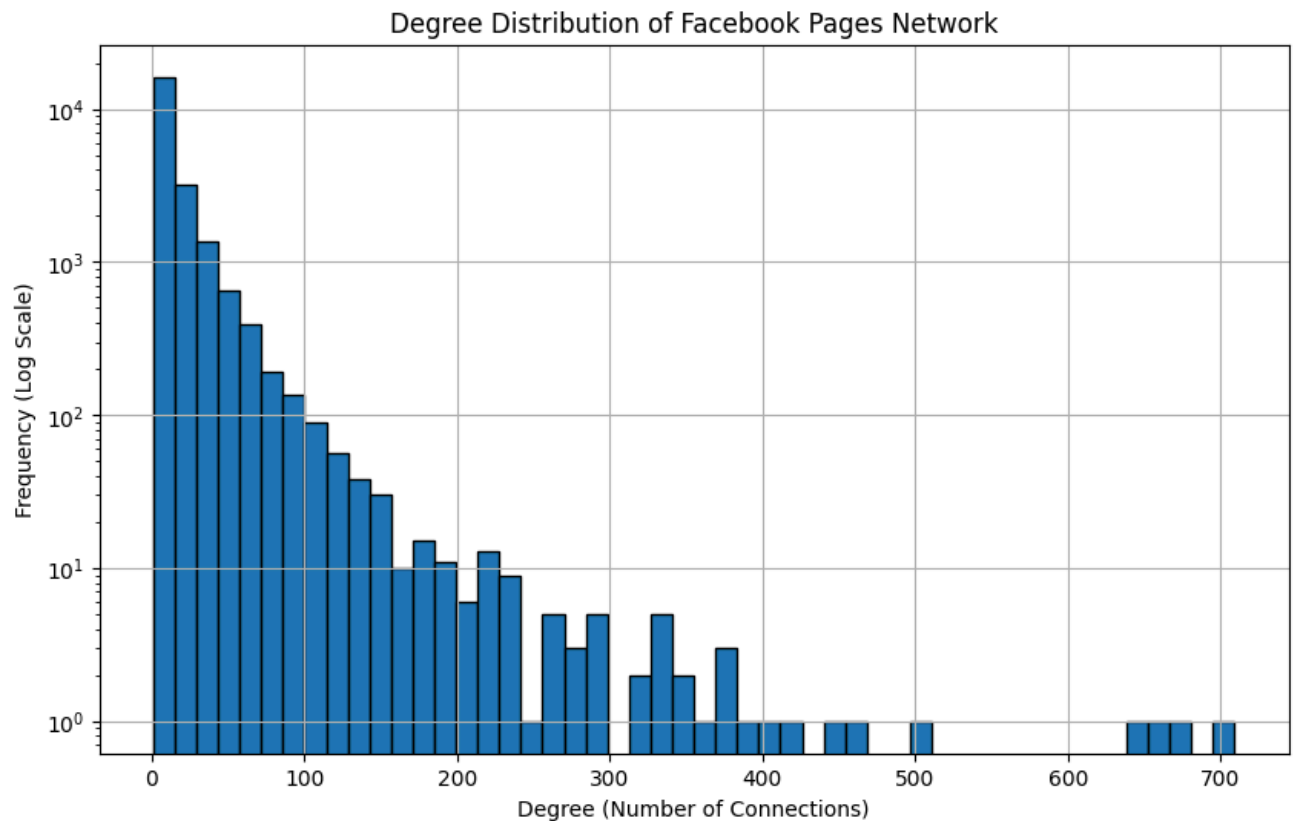
1. Most Influential Nodes - Centrality Measures

```
def analyze_central_nodes(G):
    degree centrality = nx.degree_centrality(G)
    betweenness centrality = nx.betweenness_centrality(G, k=100)
    eigenvector centrality = nx.eigenvector_centrality(G, max_iter=500)


    # Top 10 nodes for each centrality measure
    top_degree = sorted(degree_centrality.items(), key=lambda x: x[1], reverse=True)[:10]
    top_betweenness = sorted(betweenness_centrality.items(), key=lambda x: x[1], reverse=True)[:10]
    top_eigenvector = sorted(eigenvector_centrality.items(), key=lambda x: x[1], reverse=True)[:10]

    return {
        "Top Degree Centrality": top_degree,
        "Top Betweenness Centrality": top_betweenness,
        "Top Eigenvector Centrality": top_eigenvector
    }
```

```
# 2. Degree Distribution  
plot_degree_distribution(G)
```

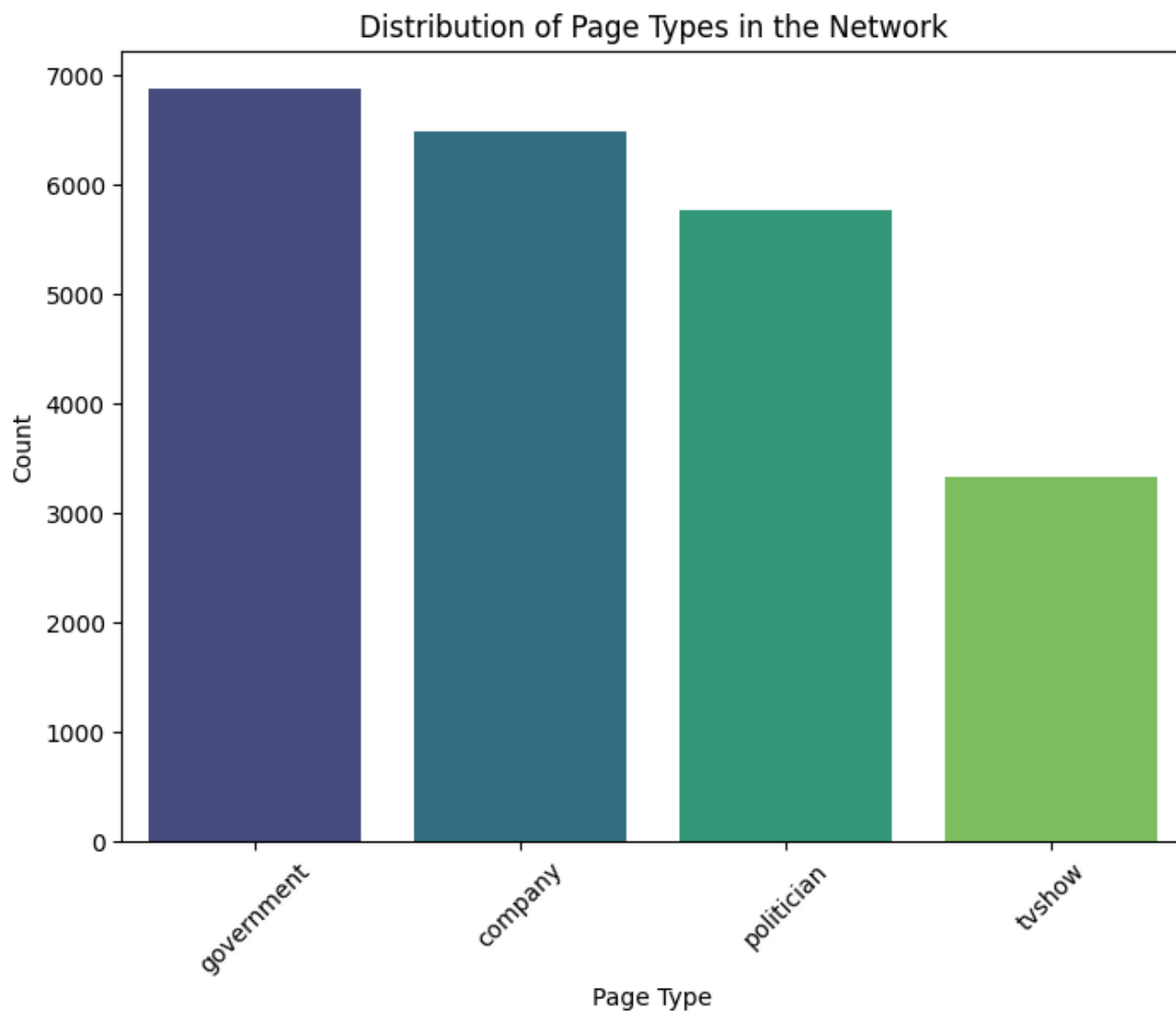


```
# 3. Page Type Distribution  
page_type_counts = large_df["page_type"].value_counts()  
plt.figure(figsize=(8, 6))  
sns.barplot(x=page_type_counts.index, y=page_type_counts.values, palette="viridis")  
plt.xlabel("Page Type")  
plt.ylabel("Count")  
plt.title("Distribution of Page Types in the Network")  
plt.xticks(rotation=45)  
plt.show()
```

 <ipython-input-14-ee95ad4e4648>:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.

```
sns.barplot(x=page_type_counts.index, y=page_type_counts.values, palette="viridis")
```



4. Largest Connected Component

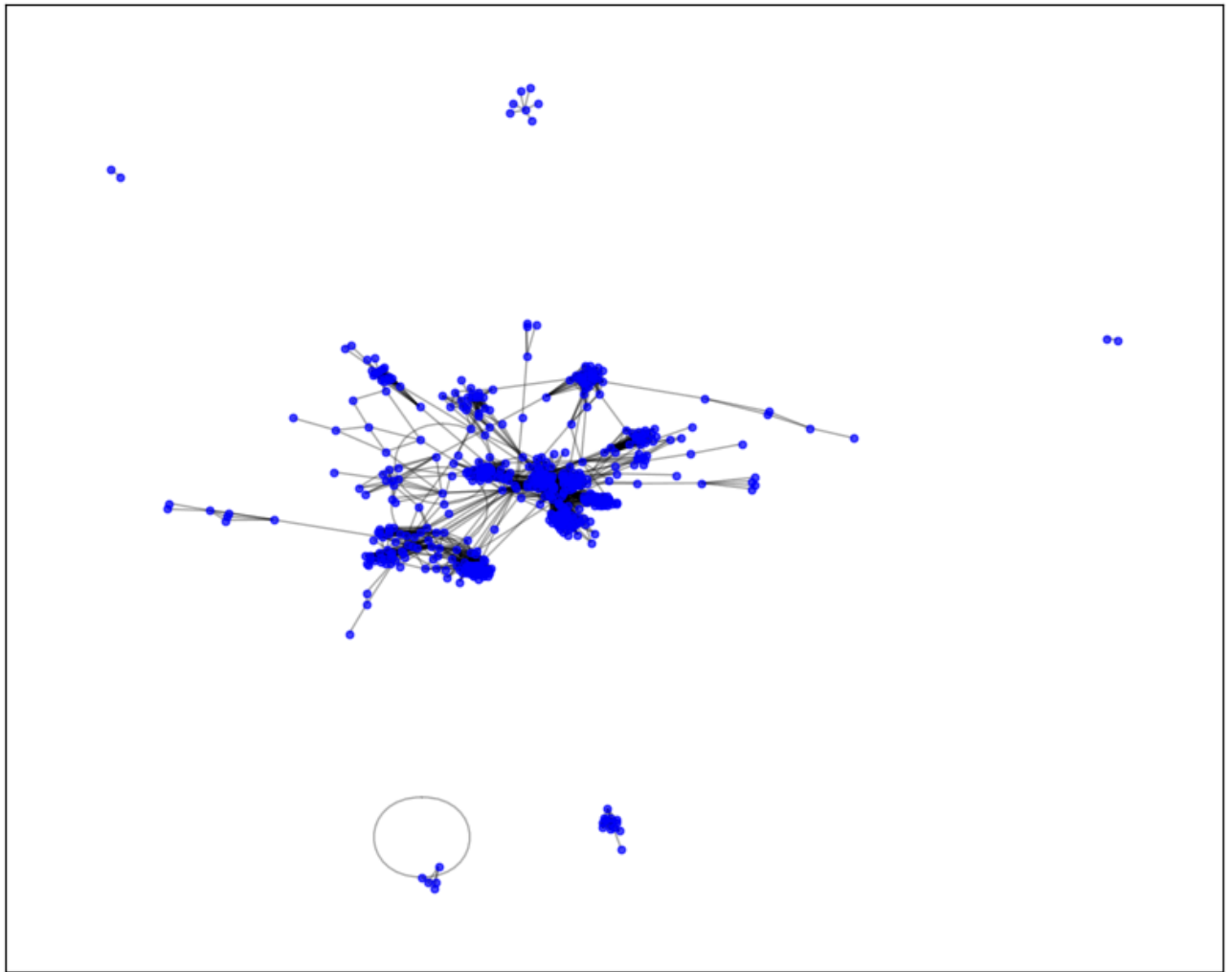
```
largest_component_nodes = max(nx.connected_components(G), key=len)
```

```
subgraph_largest_component = G.subgraph(largest_component_nodes)
```

```
plot_network_structure(subgraph_largest_component, "Largest Connected Component")
```



Largest Connected Component



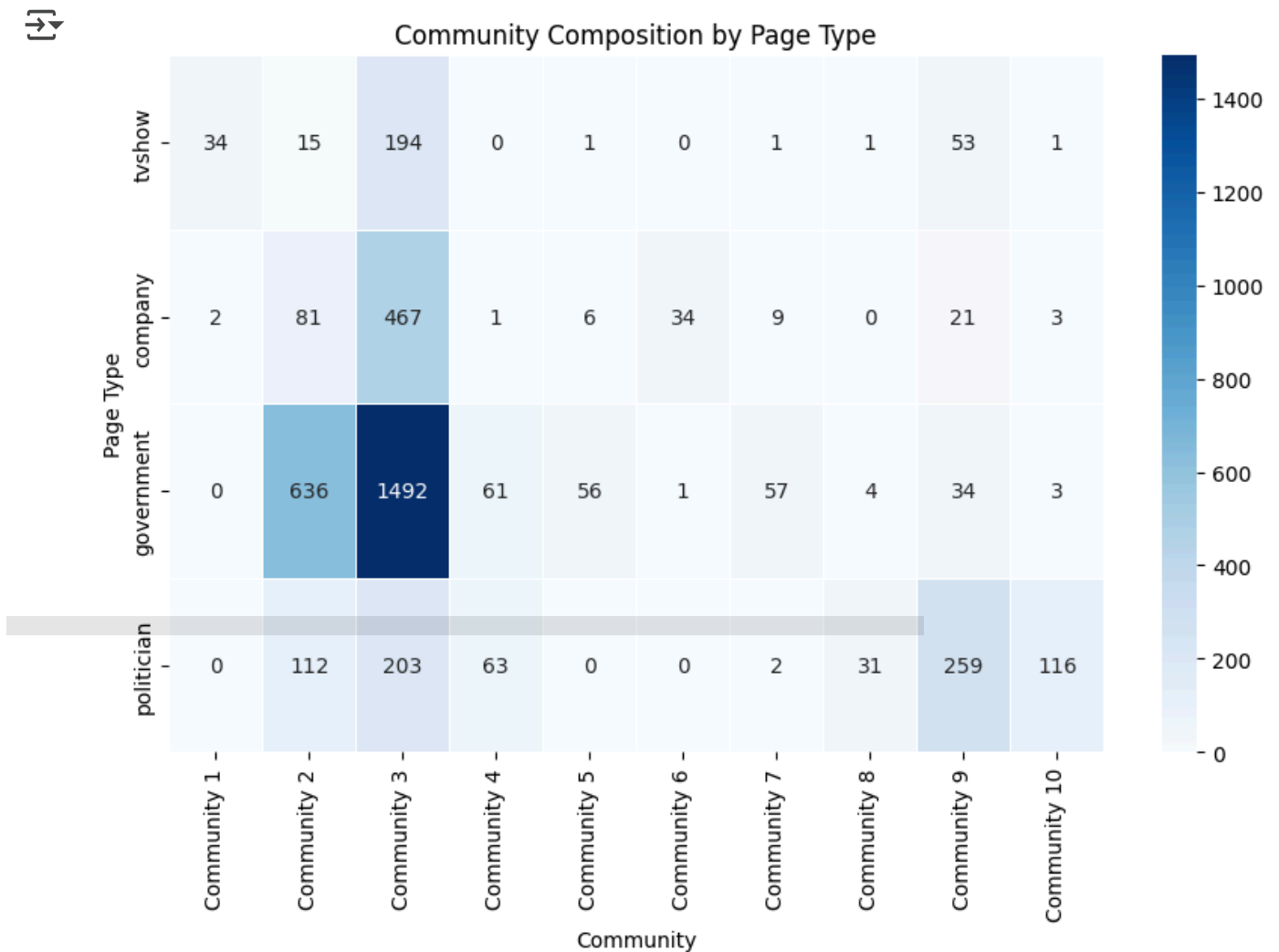
5. Community Detection & Structure

```
lpa_communities = list(nx.community.asyn_lpa_communities(G))
num_communities_lpa = len(lpa_communities)
community_sizes_lpa = sorted([len(c) for c in lpa_communities], reverse=True)[:10]

# Community composition visualization
community_page_type_counts = {}
for i, community in enumerate(lpa_communities[:10]):
    community_types = [node_attributes[node]["page_type"] if node in node_attributes else
                        community_page_type_counts[f"Community {i+1}"] = dict(Counter(community_types))

community_page_type_df = pd.DataFrame(community_page_type_counts).fillna(0)
plt.figure(figsize=(10, 6))
sns.heatmap(community_page_type_df, annot=True, fmt=".0f", cmap="Blues", linewidths=0.5)
plt.xlabel("Community")
plt.ylabel("Page Type")
plt.title("Community Composition by Page Type")
```

```
plt.show()
```



```
# 6. Inter-Community Connectivity
community_graph = nx.Graph()
node_to_community = {node: f"Community {i+1}" for i, community in enumerate(lpa_communiti

for edge in G.edges():
    if edge[0] in node_to_community and edge[1] in node_to_community:
        comm1, comm2 = node_to_community[edge[0]], node_to_community[edge[1]]
        if comm1 != comm2:
            if community_graph.has_edge(comm1, comm2):
                community_graph[comm1][comm2]["weight"] += 1
            else:
                community_graph.add_edge(comm1, comm2, weight=1)

plt.figure(figsize=(8, 6))
pos = nx.spring_layout(community_graph, seed=42)
edges, weights = zip(*nx.get_edge_attributes(community_graph, "weight").items())
```

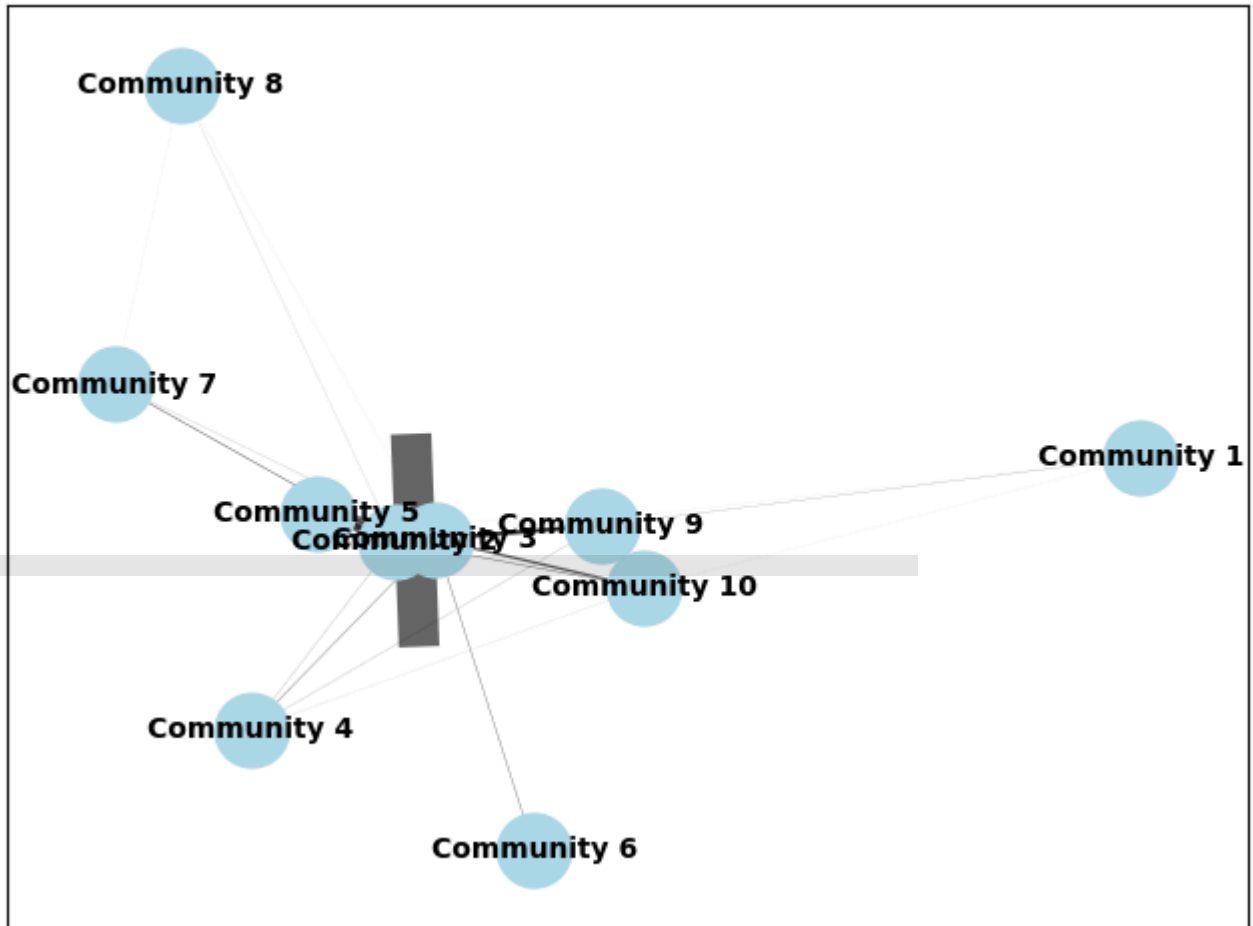
```

nx.draw_networkx_nodes(community_graph, pos, node_size=700, node_color="lightblue")
nx.draw_networkx_edges(community_graph, pos, edgelist=edges, width=[w / 50 for w in weigh
nx.draw_networkx_labels(community_graph, pos, font_size=10, font_weight="bold")
plt.title("Inter-Community Connectivity")
plt.show()

```



Inter-Community Connectivity



```

# 7. Network Density
network_density = nx.density(G)
print(f"Network Density: {network_density} (Sparse Network)")

```



Network Density: 0.000677398715568023 (Sparse Network)

```

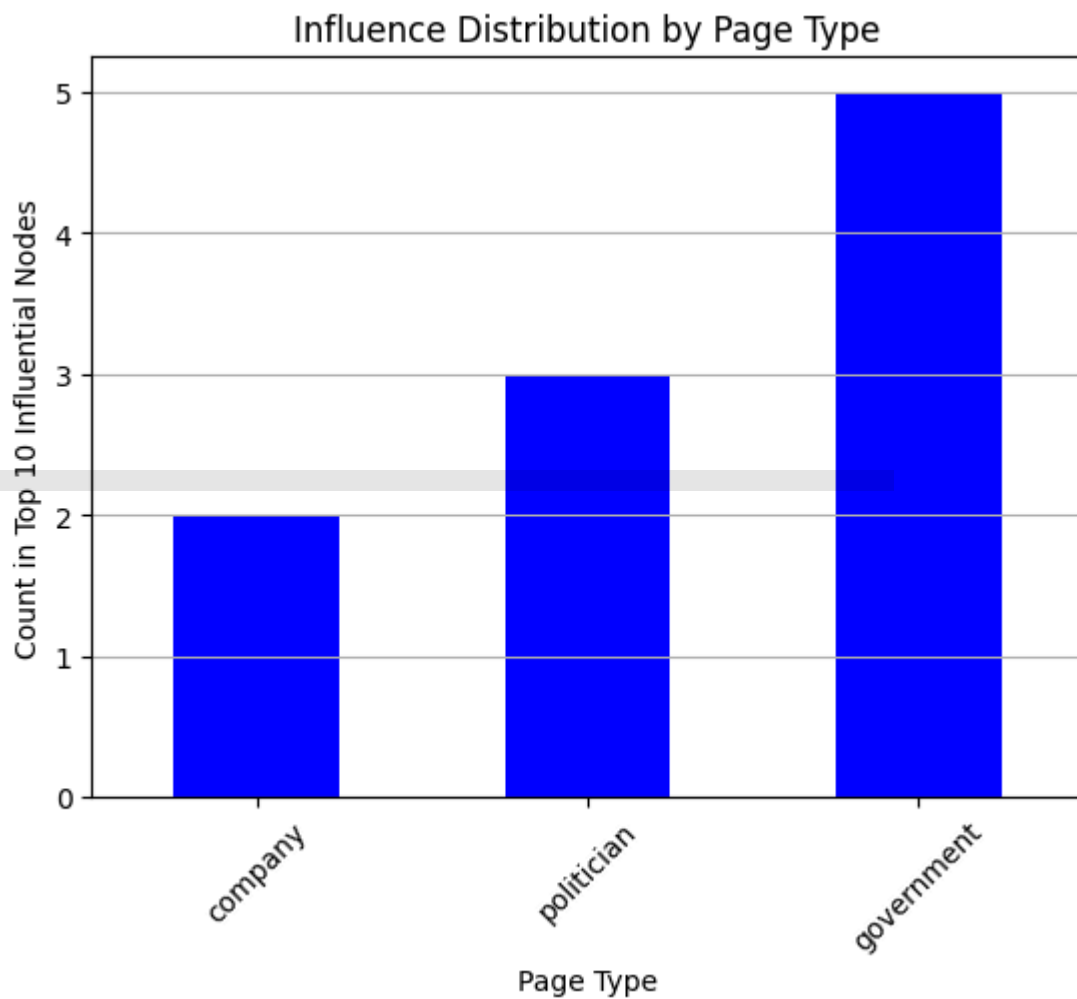
# 8. Most Influential Page Types
top_degree_nodes = [node for node, _ in analyze_central_nodes(G)["Top Betweenness Central
top_page_types = [node_attributes[node]["page_type"] if node in node_attributes else "Unk
top_page_type_counts = Counter(top_page_types)

# Convert to DataFrame for visualization
top_page_type_df = pd.DataFrame.from_dict(top_page_type_counts, orient="index", columns=[
top_page_type_df.plot(kind="bar", legend=False, color=["blue", "green", "red"])
plt.xlabel("Page Type")
plt.ylabel("Count in Top 10 Influential Nodes")
plt.title("Influence Distribution by Page Type")
plt.xticks(rotation=45)
plt.grid(axis="y")

```



```
plt.show()
```



```
# 9. Page Type Clustering in Communities
```

```
plt.figure(figsize=(10, 6))
```

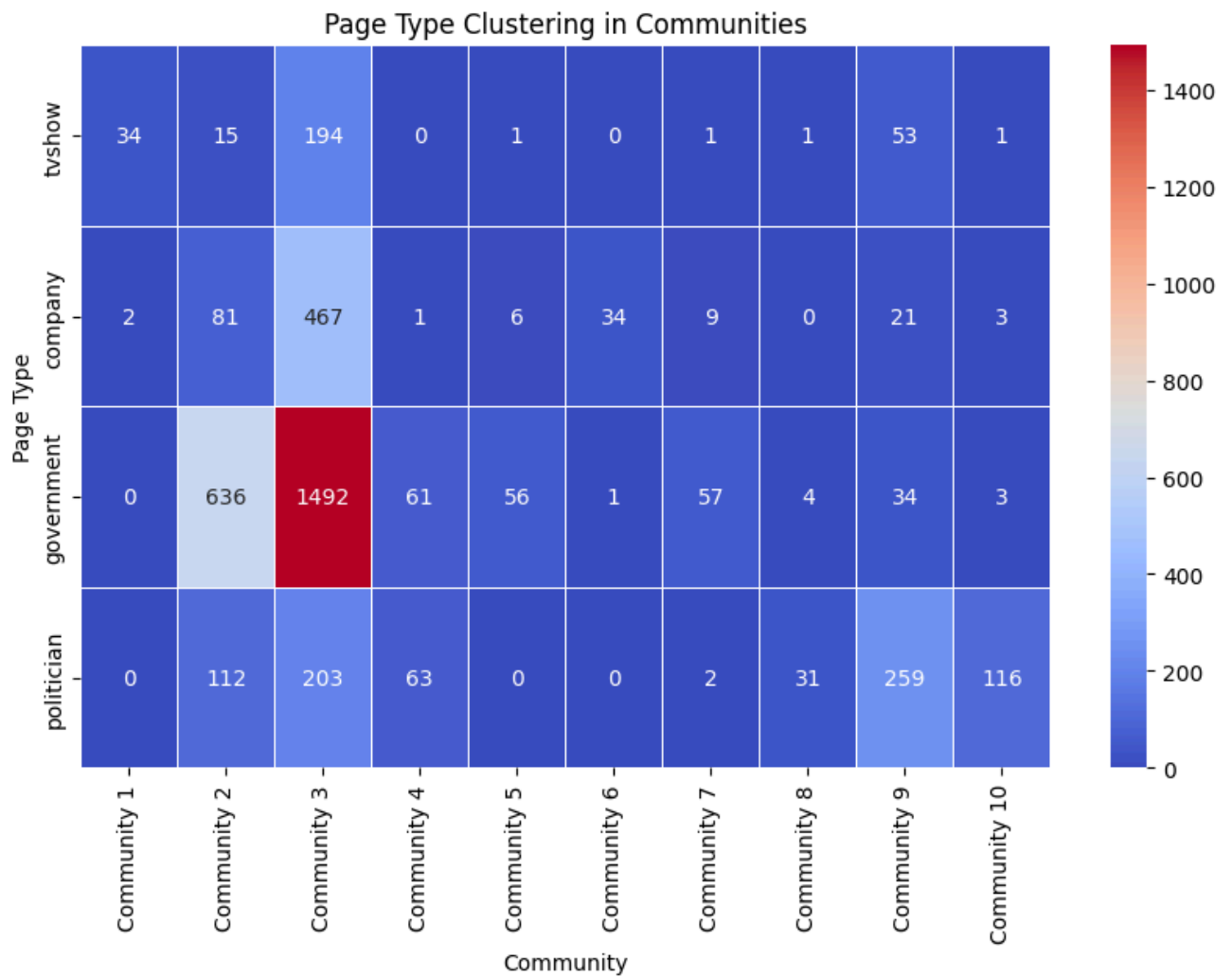
```
sns.heatmap(community_page_type_df, annot=True, fmt=".0f", cmap="coolwarm", linewidths=0.
```

```
plt.xlabel("Community")
```

```
plt.ylabel("Page Type")
```

```
plt.title("Page Type Clustering in Communities")
```

```
plt.show()
```



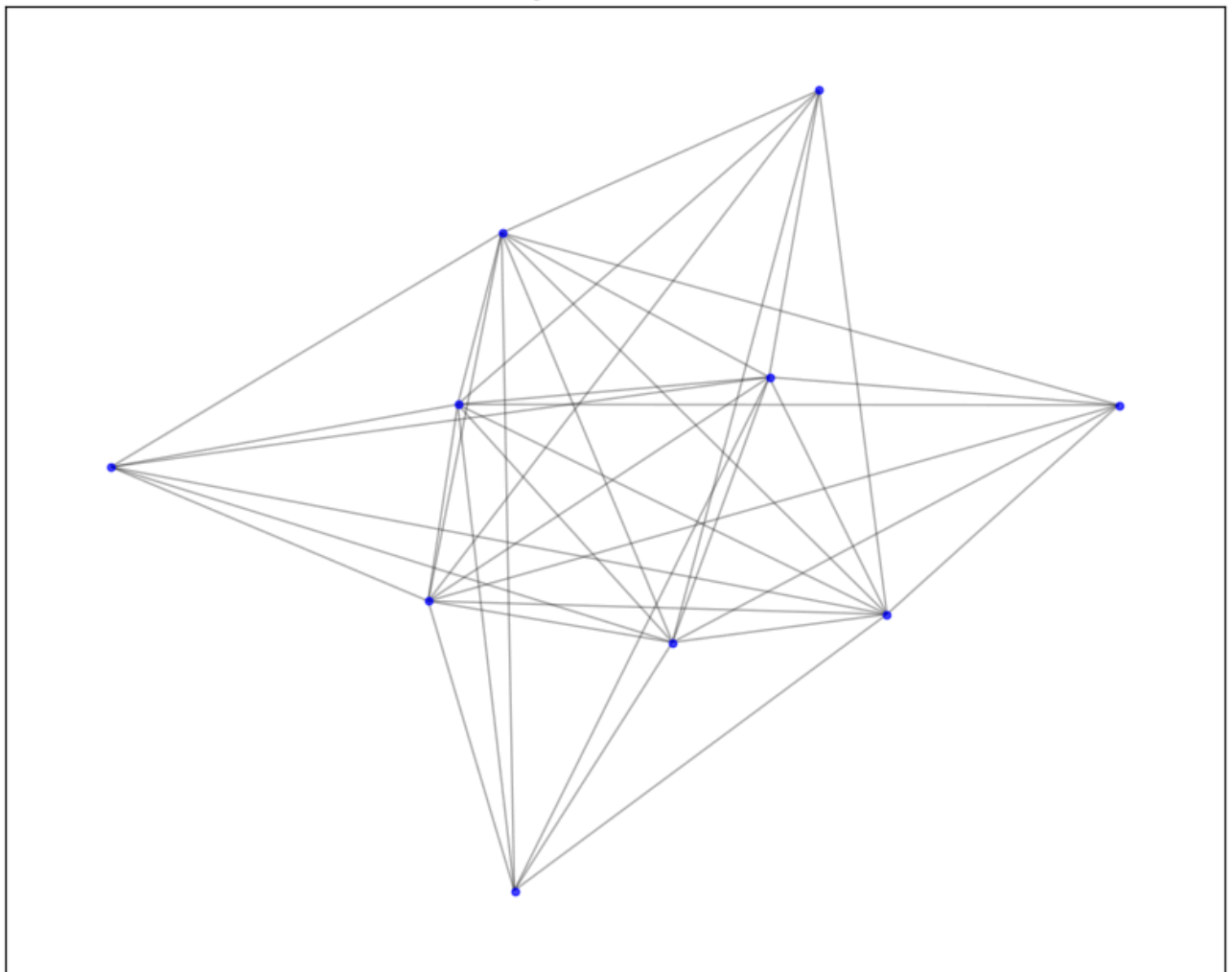
```
# 10. Connectivity of Most Central Nodes
```

```
top_central_nodes = [node for node, _ in analyze_central_nodes(G)["Top Eigenvector Centra  
subgraph_central_nodes = G.subgraph(top_central_nodes)
```

```
plot_network_structure(subgraph_central_nodes, "Connectivity of Most Central Nodes")
```



Connectivity of Most Central Nodes



```
from networkx.algorithms.community import label_propagation_communities

# Perform fast community detection using Label Propagation
communities = list(label_propagation_communities(G))
community_dict = {node: i for i, community in enumerate(communities) for node in community}

# Load node attributes (pages types)
# This line was missing or not executed correctly
node_attributes = large_df.set_index('id')[['page_name', 'page_type']].to_dict('index')

# Create centrality DataFrame (Assuming 'Node', 'Industry', 'Degree' are relevant columns)
# Replace with your actual centrality data
centrality_data = []
for node in G.nodes():
    centrality_data.append({
        'Node': node,
        'Industry': node_attributes.get(node, {}).get('page_type', 'Unknown'), # Get in
        'Degree': G.degree(node)
```

```

    })
    centrality_df = pd.DataFrame(centrality_data)

    # Add community labels to the centrality DataFrame
    centrality_df["Community"] = centrality_df["Node"].map(community_dict)

    # Display detected communities
    # Instead of tools.display_dataframe_to_user, display the dataframe directly
    print("Community Detection Results:") # Print a header
    print(centrality_df.head()) # Print the head of the DataFrame

    # Aggregate by industry and community
    industry_community = centrality_df.groupby(["Industry", "Community"])["Degree"].mean().reset_index()
    industry_community = industry_community.nlargest(10, "Degree")

    # Plot Top 10 Most Connected Industries with Community Labels
    plt.figure(figsize=(12, 6))
    sns.barplot(data=industry_community, x="Industry", y="Degree", hue="Community", dodge=True)
    plt.xticks(rotation=45, ha="right")
    plt.xlabel("Industry")
    plt.ylabel("Average Degree Centrality")
    plt.title("Top 10 Most Connected Industries with Community Labels")
    plt.legend(title="Community")
    plt.show()

    # Identify Most Influential Nodes in Each Community
    top_nodes_per_community = centrality_df.groupby("Community").apply(lambda x: x.nlargest(10, "Degree"))
    # Instead of tools.display_dataframe_to_user, display the dataframe directly
    print("Top Influential Nodes per Community:") # Print a header
    print(top_nodes_per_community) # Print the DataFrame

```



Community Detection Results:

	Node	Industry	Degree	Community
0	0	tvshow	1	0
1	18427	tvshow	51	0
2	1	government	34	1
3	21708	government	195	1
4	22208	government	205	1

Top 10 Most Connected Industries with Community Labels

