```
import networkx as nx
import numpy as np
import matplotlib.pyplot as plt
import random
import os
```

→ Loaded network with 30918 nodes and 1708952 edges

```
# Approximate Clustering for Faster Computation
sample_nodes = random.sample(list(G.nodes()), min(1000, len(G.nodes())))
approx_clustering_coeff = nx.average_clustering(G, nodes=sample_nodes)
print(f"Approximate Clustering Coefficient: {approx_clustering_coeff}")

# Global Clustering Coefficient (Faster Alternative)
global_clustering = nx.transitivity(G)
print(f"Global Clustering Coefficient: {global_clustering}")

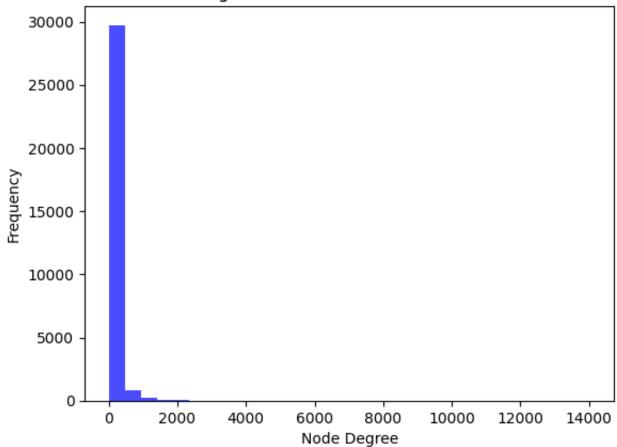
# Compute Network Density
print(f"Network Density: {nx.density(G)}")
```

Approximate Clustering Coefficient: 0.27512942139385266 Global Clustering Coefficient: 0.0560354733068454 Network Density: 0.0035756180548324524

```
# Visualize Degree Distribution
degree_sequence = [d for n, d in G.degree()]
plt.hist(degree_sequence, bins=30, color="blue", alpha=0.7)
plt.xlabel("Node Degree")
plt.ylabel("Frequency")
plt.title("Degree Distribution of the Network")
plt.show()
```



Degree Distribution of the Network



!apt-get install -y mcl

Reading package lists... Done
Building dependency tree... Done
Reading state information... Done
mcl is already the newest version (1:14-137+ds-9build2).
0 upgraded, 0 newly installed, 0 to remove and 29 not upgraded.

```
# Save the network in MCL-compatible format
edge_list_file = "network_mcl.txt"
nx.write_edgelist(G, edge_list_file, data=False)
print(f"Network saved to {edge_list_file} for MCL processing.")
```

Network saved to network_mcl.txt for MCL processing.

Run MCL with default settings (adjust --I for inflation factor tuning) !mcl network_mcl.txt --abc -o clusters.txt -I 1.8

```
\rightarrow
    [mcl] new tab created
    [mcl] pid 9027
    ite -----
                                time hom(avg,lo,hi) m-ie m-ex i-ex fmv
                          chaos
        2
          3
                                                                  99
                          22.92
                                8.92 0.86/0.09/4.25 4.87 0.18 0.27
     5
                           9.31
                                0.61 0.93/0.23/2.93 2.08 0.25 0.07
                           4.61
                                0.10 0.96/0.22/2.42 1.42 0.61 0.04
     7
                                0.06 0.97/0.32/1.84 1.08 0.84 0.03
                           2.54
     8
                           2.47
                                0.05 0.98/0.32/2.05 1.02 0.92 0.03
                           2.10
     9
                                0.05 0.99/0.43/1.39 1.01 0.96 0.03
    10
                           1.80
                                0.05 0.98/0.41/1.00 1.01 0.93 0.03
                                0.04 0.94/0.43/1.00 1.00 0.99 0.03
    11
                           1.32
                                0.05 0.84/0.47/1.00 1.00 0.99 0.03
    12
                           1.04
    13
                           1.16
                                0.04 0.71/0.52/1.00 1.00 1.00 0.03
    14
                                0.04 0.71/0.50/1.00 1.00 1.00 0.03
                           0.99
    15
                           0.75
                                0.04 0.89/0.68/1.00 1.00 0.99 0.03
                                0.04 0.99/0.76/1.00 1.00 1.00 0.03
    16
                           0.61
    17
                           0.23
                                0.04 1.00/0.77/1.00 1.00 0.32 0.01
    18
                           0.22
                                0.03 1.00/0.82/1.00 1.00 1.00 0.01
    19
                           0.25
                                0.03 1.00/0.76/1.00 1.00 1.00 0.01
    20
                                0.03 1.00/0.84/1.00 1.00 1.00 0.01
                           0.16
    21
                           0.23
                                0.03 1.00/0.81/1.00 1.00 1.00 0.01
    22
                           0.25
                                0.03 1.00/0.76/1.00 1.00 1.00 0.01
    23
                           0.15
                                0.03 1.00/0.85/1.00 1.00 1.00 0.01
    24
                           0.03
                                0.03 1.00/0.97/1.00 1.00 1.00 0.01
    25
                                0.03 1.00/1.00/1.00 1.00 1.00 0.01
                           0.00
                                                                 0
    26
                           0.00
                                0.03 1.00/1.00/1.00 1.00 1.00 0.01
           . . . . . . . . . . . . . . . .
    [mcl] jury pruning marks: <28,77,96>, out of 100
    [mcl] jury pruning synopsis: <48.8 or off colour> (cf -scheme, -do log)
    [mcl] output is in clusters.txt
```

```
[mcl] 467 clusters found
[mcl] output is in clusters.txt

Please cite:
    Stijn van Dongen, Graph Clustering by Flow Simulation. PhD thesis,
    University of Utrecht, May 2000.
        ( http://www.library.uu.nl/digiarchief/dip/diss/1895620/full.pdf
        or http://micans.org/mcl/lit/svdthesis.pdf.gz)

OR
    Stijn van Dongen, A cluster algorithm for graphs. Technical
    Report INS-R0010, National Research Institute for Mathematics
    and Computer Science in the Netherlands, Amsterdam, May 2000.
        ( http://www.cwi.nl/ftp/CWIreports/INS/INS-R0010.ps.Z
        or http://micans.org/mcl/lit/INS-R0010.ps.Z)
```

```
# Read MCL clusters from the output file
clusters = []
with open("clusters.txt", "r") as f:
    for line in f:
        cluster = line.strip().split("\t")
        clusters.append(cluster)

# Print number of clusters detected
print(f"Number of clusters detected: {len(clusters)}")

# Display the first 5 clusters
for i, cluster in enumerate(clusters[:5]):
    print(f"Cluster {i+1}: {cluster}")

Number of clusters detected: 467
    Cluster 1: ['A1BG'. 'A2M'. 'ADAM10'. 'ADAM17'. 'ADAM9'. 'AGO1'. 'ANXA7'. 'CRIS
```

```
Cluster 1: ['A1BG', 'A2M', 'ADAM10', 'ADAM17', 'ADAM9', 'AG01', 'ANXA7', 'CRISC Cluster 2: ['ABCC6', 'AKT1', 'CDKN1A', 'GCLC', 'CASP3', 'CASP9', 'CTSB', 'MMPSC Cluster 3: ['CYP2C18', 'CYP2C8', 'LCAT', 'CHEBI:3687', 'CHEBI:5356', 'CYP2A13C Cluster 4: ['OR4S2', 'GNB1', 'GNGT1', 'OR14I1', 'OR6T1', 'REEP1', 'REEP4', 'RCC Cluster 5: ['CPT2', 'HADHB', 'ACADS', 'CPT1A', 'HADHA', 'ELOVL5', 'PANK1', 'P/OR14I1', 'P/OR14I1', 'P/OR14I1', 'P/OR14I1', 'P/OR14I1', 'P/OR14I1', 'P/OR14I1', 'P/OR14I1', 'P/OR14I1', 'P/OR14II', 'P/OR14I
```

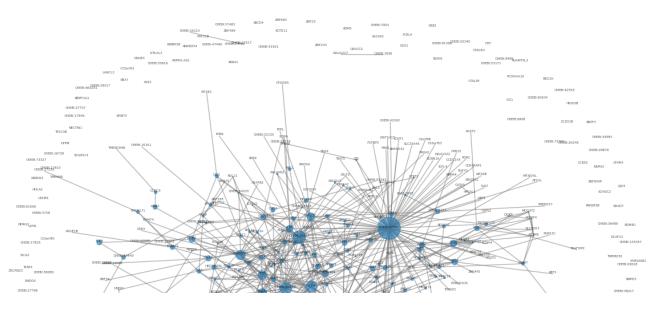
```
import networkx as nx
import matplotlib.pyplot as plt
import numpy as np
import random

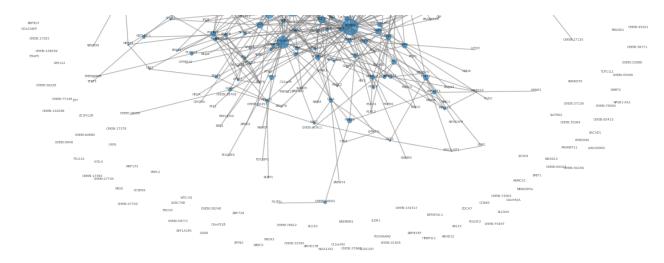
# Pick a sample cluster
sample_cluster_nodes = clusters[0] # Select first cluster
subgraph = G.subgraph(sample_cluster_nodes)
```

```
# Ensure the cluster is connected (some clusters may be fragmented)
if nx.is connected(subgraph):
    largest cc = subgraph
else:
    largest_cc = max(nx.connected_components(subgraph), key=len)
    subgraph = G.subgraph(largest_cc)
# / **Speed Boost: Limit to 500 Nodes for Faster Visualization**
if len(subgraph.nodes()) > 500:
    sample_nodes = random.sample(list(subgraph.nodes()), 500)
    subgraph = G.subgraph(sample_nodes)
# > **Faster Layout Calculation with Better Node Spacing**
pos = nx.spring_layout(subgraph, seed=42, k=0.2) # Higher k spreads nodes out
# # **Compute node centrality (betweenness) to scale node sizes**
centrality = nx.betweenness centrality(subgraph)
node_sizes = np.array([centrality[n] for n in subgraph.nodes()]) * 5000 # Scale |
# / **Optimized Plotting with Centrality-Based Node Sizing**
plt.figure(figsize=(12, 10))
nx.draw(subgraph, pos, with_labels=False, node_size=node_sizes, edge_color="gray"
nx.draw_networkx_labels(subgraph, pos, font_size=4, alpha=0.7, verticalalignment=
plt.title("Enhanced Visualization with Centrality-Based Node Sizing")
plt.show()
```

→

Enhanced Visualization with Centrality-Based Node Sizing





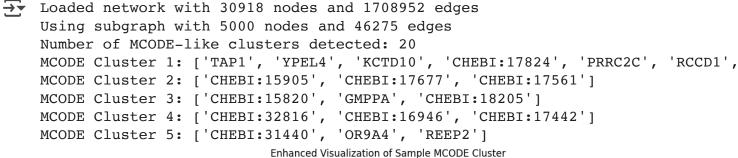
MCODE

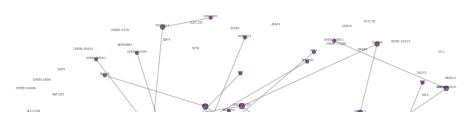
```
import networkx as nx
import numpy as np
import matplotlib.pyplot as plt
import random
import os
import matplotlib.cm as cm
from networkx.algorithms.community import k_clique_communities
# Corrected File Path
```

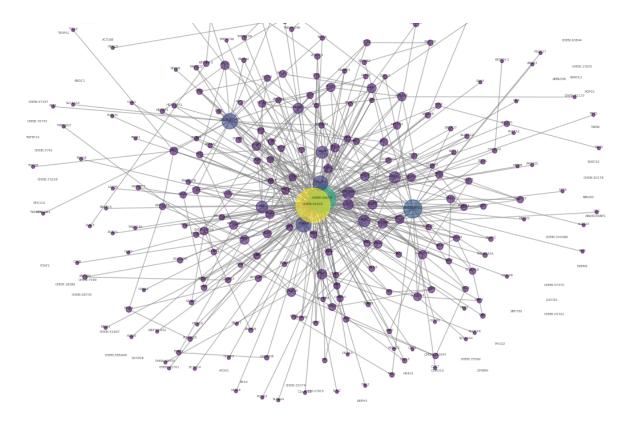
```
file_path = "/content/PathwayCommons12.All.hgnc.sif" # Adjust if needed
# Initialize an empty graph
G = nx.Graph()
# Read the SIF file and build the graph
with open(file_path, "r") as f:
    for line in f:
        parts = line.strip().split("\t")
        if len(parts) == 3: # Ensure correct format (source, interaction, target
            source, interaction, target = parts
            G.add_edge(source, target) # Adding only interacting proteins
# Check if graph loaded correctly
print(f"Loaded network with {G.number_of_nodes()} nodes and {G.number_of_edges()}
# **Step 1: Reduce Graph Size for Faster MCODE Execution**
num nodes = 5000 # Adjust this number based on performance
sample_nodes = random.sample(list(G.nodes()), num_nodes)
subgraph = G.subgraph(sample_nodes)
print(f"Using subgraph with {subgraph.number_of_nodes()} nodes and {subgraph.number_of_nodes()}
# **Step 2: Run MCODE Approximation (k-Clique Method) on Reduced Graph**
k = 3 # Smaller value = faster computation
# Run MCODE-like clustering
clique_communities = list(k_clique_communities(subgraph, k))
# Convert detected communities to list format
mcode_clusters = [list(community) for community in clique_communities]
print(f"Number of MCODE-like clusters detected: {len(mcode_clusters)}")
# Print first 5 detected clusters
for i, cluster in enumerate(mcode_clusters[:5]):
    print(f"MCODE Cluster {i+1}: {cluster}")
# **Step 3: Visualize a Sample MCODE Cluster**
# Pick a sample MCODE cluster
sample_mcode_nodes = mcode_clusters[0] # Select first cluster
subgraph_mcode = subgraph.subgraph(sample_mcode_nodes)
# Ensure the cluster is connected
if nx.is_connected(subgraph_mcode):
```

largest cc mcode = subgraph mcode

```
else:
    largest cc mcode = max(nx.connected components(subgraph mcode), key=len)
    subgraph mcode = subgraph.subgraph(largest cc mcode)
# / **Limit the number of nodes for better visualization**
if len(subgraph mcode.nodes()) > 300:
    sample_nodes = random.sample(list(subgraph_mcode.nodes()), 300)
    subgraph_mcode = subgraph_mcode.subgraph(sample_nodes)
# Faster Layout Calculation
pos_mcode = nx.spring_layout(subgraph_mcode, seed=42, k=0.4) # Higher k spreads |
# Compute node degree centrality for sizing and coloring
degree_centrality = nx.degree_centrality(subgraph_mcode)
node_sizes_mcode = np.array([degree_centrality[n] for n in subgraph_mcode.nodes()
# Normalize for colormap
norm = plt.Normalize(vmin=min(degree_centrality.values()), vmax=max(degree_centrality.values())
colors = [cm.viridis(norm(degree_centrality[n])) for n in subgraph_mcode.nodes()]
# Optimized Plot
plt.figure(figsize=(12, 10))
nx.draw(subgraph_mcode, pos_mcode, with_labels=False, node_size=node_sizes_mcode,
nx.draw_networkx_labels(subgraph_mcode, pos_mcode, font_size=4, alpha=0.7, vertice
plt.title("Enhanced Visualization of Sample MCODE Cluster")
plt.show()
→▼ Loaded network with 30918 nodes and 1708952 edges
```







lets Perform biological analysis of the clusters.

```
# Check if clusters exist, otherwise reload from saved files
if 'clusters' not in globals():
    print(".! MCL clusters not found! Reloading clusters from file...")
    clusters = []
    with open("clusters.txt", "r") as f:
        for line in f:
            cluster = line.strip().split("\t")
            clusters.append(cluster)

if 'mcode_clusters' not in globals():
    print(".! MCODE clusters not found! Re-running MCODE clustering...")
    from networkx.algorithms.community import k_clique_communities
    k = 3  # Minimum clique size
    clique_communities = list(k_clique_communities(G, k))
    mcode_clusters = [list(community) for community in clique_communities]
```

```
from collections import Counter
# Function to extract hub nodes from a cluster
def get_hub_nodes(cluster, G, top_n=5):
    degrees = {node: G.degree(node) for node in cluster}
     sorted_nodes = sorted(degrees.items(), key=lambda x: x[1], reverse=True)
     return [node for node, _ in sorted_nodes[:top_n]]
# Get top 5 clusters from MCL and MCODE
top mcl clusters = clusters[:5] # From MCL
top_mcode_clusters = mcode_clusters[:5] # From MCODE
# Extract hub nodes
hub_nodes_mcl = [get_hub_nodes(cluster, G) for cluster in top_mcl_clusters]
hub_nodes_mcode = [get_hub_nodes(cluster, G) for cluster in top_mcode_clusters]
# Print hub nodes
for i, hubs in enumerate(hub_nodes_mcl):
    print(f" ◆ MCL Cluster {i+1} Hub Nodes: {hubs}")
for i, hubs in enumerate(hub_nodes_mcode):
     print(f" 	◆ MCODE Cluster {i+1} Hub Nodes: {hubs}")
     MCL Cluster 1 Hub Nodes: ['CHEBI:39867', 'CHEBI:4667', 'CHEBI:60654', 'CHE
       MCL Cluster 2 Hub Nodes: ['PTK2', 'CASP3', 'RELA', 'AKT1', 'PARP1']
       MCL Cluster 3 Hub Nodes: ['CYP3A4', 'CYP2C19', 'CYP2C9', 'CYP2D6', 'NCOA1'

MCL Cluster 4 Hub Nodes: ['GNB1', 'GNGT1', 'GNAL', 'REEP4', 'REEP5']

MCL Cluster 5 Hub Nodes: ['ACSL1', 'HADHB', 'CHEBI:57287', 'CPT1A', 'HADHA

MCODE Cluster 1 Hub Nodes: ['CHEBI:60654', 'CHEBI:31522', 'CHEBI:31440', 'MCODE Cluster 2 Hub Nodes: ['CHEBI:17677', 'CHEBI:17561', 'CHEBI:15905']
       MCODE Cluster 3 Hub Nodes: ['GMPPA', 'CHEBI:15820', 'CHEBI:18205']
        MCODE Cluster 4 Hub Nodes: ['CHEBI:32816', 'CHEBI:16946', 'CHEBI:17442']
         MCODE Cluster 5 Hub Nodes: ['CHEBI:31440', 'REEP2', 'OR9A4']
```

Next to compare MCL and MCODE Clustering

Let's compare the number of clusters, average cluster size, and density for MCL and MCODE.

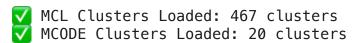
```
# Function to calculate basic cluster statistics
def cluster_statistics(cluster_list, G):
    cluster_sizes = [len(cluster) for cluster in cluster_list]
    avg_size = sum(cluster_sizes) / len(cluster_sizes)
    max_size = max(cluster_sizes)
```

```
min_size = min(cluster_sizes)
           densities = [nx.density(G.subgraph(cluster)) for cluster in cluster list if leading to the control of the contr
           avg density = sum(densities) / len(densities) if densities else 0
            return len(cluster_list), avg_size, max_size, min_size, avg_density
# Compute stats for MCL
num_mcl, avg_mcl_size, max_mcl, min_mcl, avg_mcl_density = cluster_statistics(cluster)
# Compute stats for MCODE
num_mcode, avg_mcode_size, max_mcode, min_mcode, avg_mcode_density = cluster_stat
# Print the results
print(f" 	MCL Clustering Stats:")
print(f"- Number of Clusters: {num mcl}")
print(f"- Avg Cluster Size: {avg_mcl_size:.2f}")
print(f"- Max Cluster Size: {max mcl}")
print(f"- Min Cluster Size: {min mcl}")
print(f"- Avg Cluster Density: {avg_mcl_density:.4f}\n")
print(f" 	MCODE Clustering Stats:")
print(f"- Number of Clusters: {num_mcode}")
print(f"- Avg Cluster Size: {avg_mcode_size:.2f}")
print(f"- Max Cluster Size: {max_mcode}")
print(f"- Min Cluster Size: {min mcode}")
print(f"- Avg Cluster Density: {avg_mcode_density:.4f}")
```

- → MCL Clustering Stats:
 - Number of Clusters: 467
 - Avg Cluster Size: 66.21
 - Max Cluster Size: 21541
 - Min Cluster Size: 1
 - Avg Cluster Density: 0.5219
 - MCODE Clustering Stats:
 - Number of Clusters: 20
 - Avg Cluster Size: 157.20
 - Max Cluster Size: 3079
 - Min Cluster Size: 3
 - Avg Cluster Density: 0.8871

```
import os
import networkx as nx
from networkx.algorithms.community import k_clique_communities
# Ensure the graph is loaded
if 'G' not in globals():
    raise ValueError("1 Graph (G) is not defined. Please reload the graph before
# Reload MCL Clusters if missing
if 'clusters' not in globals():
    if os.path.exists("clusters.txt"):
        print("1 MCL clusters not found in memory! Reloading from file...")
        clusters = []
        with open("clusters.txt", "r") as f:
            for line in f:
                cluster = line.strip().split("\t")
                clusters.append(cluster)
   else:
        raise ValueError("/ clusters.txt file not found! You need to rerun MCL c
# Reload MCODE Clusters if missing
if 'mcode_clusters' not in globals():
    print("... MCODE clusters not found! Re-running MCODE clustering...")
    k = 3 # Adjust k for density
    clique_communities = list(k_clique_communities(G, k))
    mcode_clusters = [list(community) for community in clique_communities]
print(f" ✓ MCL Clusters Loaded: {len(clusters)} clusters")
print(f" ✓ MCODE Clusters Loaded: {len(mcode_clusters)} clusters")
```





```
import random

# Extract a subgraph for faster computation (limit to 5000 nodes)
if len(G.nodes) > 5000:
    sampled_nodes = random.sample(list(G.nodes), 5000)
    subG = G.subgraph(sampled_nodes).copy()
    print(f" > Using subgraph with {len(subG.nodes)} nodes and {len(subG.edges)} else:
    subG = G # Use full graph if it's already small
```

→ ✓ Using subgraph with 5000 nodes and 48854 edges

```
Execution Time for MCL (Top 5 Clusters): 0.00 seconds Execution Time for MCODE (Limited Subgraph): 911.56 seconds
```

```
# Function to calculate basic cluster statistics
def cluster_statistics(cluster_list, G):
    cluster_sizes = [len(cluster) for cluster in cluster_list]
    avg_size = sum(cluster_sizes) / len(cluster_sizes) if cluster_sizes else 0
    max_size = max(cluster_sizes) if cluster_sizes else 0
    min_size = min(cluster_sizes) if cluster_sizes else 0

densities = [nx.density(G.subgraph(cluster)) for cluster in cluster_list if ler avg_density = sum(densities) / len(densities) if densities else 0
```

```
return len(cluster_list), avg_size, max_size, min_size, avg_density
# Compute stats for MCL
num_mcl, avg_mcl_size, max_mcl, min_mcl, avg_mcl_density = cluster_statistics(clust
# Compute stats for MCODE
num mcode, avg mcode size, max mcode, min mcode, avg mcode density = cluster statis
# Print the results
print(f" → MCL Clustering Stats (Top 5 Clusters):")
print(f"- Number of Clusters: {num_mcl}")
print(f"- Avg Cluster Size: {avg_mcl_size:.2f}")
print(f"- Max Cluster Size: {max mcl}")
print(f"- Min Cluster Size: {min mcl}")
print(f"- Avg Cluster Density: {avg_mcl_density:.4f}\n")
print(f" ◆ MCODE Clustering Stats (Top 5 Clusters):")
print(f"- Number of Clusters: {num_mcode}")
print(f"- Avg Cluster Size: {avg_mcode_size:.2f}")
print(f"- Max Cluster Size: {max mcode}")
print(f"- Min Cluster Size: {min mcode}")
print(f"- Avg Cluster Density: {avg_mcode_density:.4f}")
→ MCL Clustering Stats (Top 5 Clusters):
    - Number of Clusters: 5
    - Avg Cluster Size: 4686.80
    - Max Cluster Size: 21541
    - Min Cluster Size: 337
    - Avg Cluster Density: 0.0536
    MCODE Clustering Stats (Top 5 Clusters):
    - Number of Clusters: 5
    - Ava Cluster Size: 622.60
    - Max Cluster Size: 3100
    - Min Cluster Size: 3
    - Avg Cluster Density: 0.7686
Start coding or generate with AI.
```