```
import networkx as nx
import random
import matplotlib.pyplot as plt
import numpy as np
from collections import Counter
from tqdm import tqdm

G = nx.read_edgelist('email-Eu-core.txt', create_using=nx.DiGraph())
num_nodes = G.number_of_nodes()
num_edges = G.number_of_edges()

num_nodes, num_edges
```

Out[14]: (1005, 25571)

The configuration_model function creates random directed graphs with the same indegree and out-degree sequences as the original by using networkx's directed_configuration_model, followed by removal of self-loops and parallel edges. The edge_swapping function iteratively rewires the original graph by randomly swapping edge endpoints while maintaining node degrees. Finally, plot_degree_distribution compares the degree distributions of the original graph and the randomized graphs using histograms to visualize structural similarities.

```
In [ ]: # Configuration Model: Generate random graph with the same degree sequence
        def configuration model(G, seed=None):
            Generate a random graph using the configuration model,
            preserving the in-degree and out-degree sequences.
            if seed is not None:
                np.random.seed(seed)
            in_degrees = [d for _, d in G.in_degree()]
            out_degrees = [d for _, d in G.out_degree()]
            # Generate random graph using configuration model
            R = nx.directed_configuration_model(in_degrees, out_degrees, seed=see
            # Remove parallel edges and self-loops
            R = nx.DiGraph(R)
            R.remove_edges_from(nx.selfloop_edges(R))
            return R
        # Edge-Swapping Strategy: Generate random graph with the same degree sequ
        def edge swapping(graph, instances=100):
            degree_sequence = [d for _, d in graph.degree()]
            random graphs = []
            print("Generating Random graph through Edge Swapping...")
            for in tqdm(range(instances)):
                random_graph = graph.copy()
                edges = list(random_graph.edges())
                # Edge-swapping process: swap edges randomly while keeping the de
                for i in range(len(edges) // 2):
                    u, v = edges[i]
                    w, x = edges[-(i+1)]
```

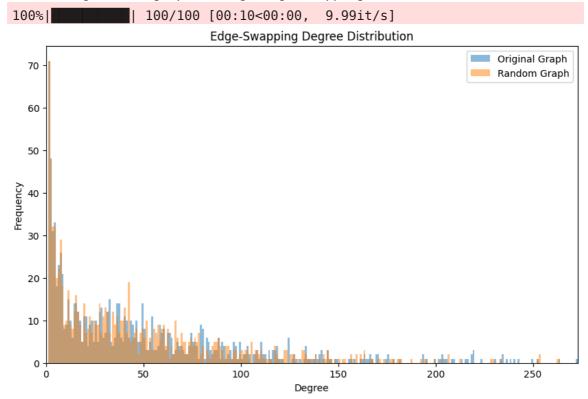
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```
random graph.remove edge(u, v)
             random graph.remove edge(w, x)
             random graph.add edge(u, x)
             random graph.add edge(w, v)
        random_graphs.append(random_graph)
    return random graphs
# Function to plot the degree distribution of the graph
def plot degree distribution(graph, random graphs, title, filename):
    degree_sequence_real = [d for _, d in graph.degree()]
    degree sequence random = np.mean([list(dict(g.degree()).values()) for
    # Ensure integer values for degrees
    degree sequence random = np.floor(degree sequence random).astype(int)
    plt.figure(figsize=(10,6))
    plt.hist(degree sequence real, bins=range(1, max(degree sequence real
    plt hist(degree sequence random, bins=range(1, max(degree sequence ra
    plt.xlabel('Degree')
    plt.ylabel('Frequency')
    plt.title(title)
    plt.legend(loc='upper right')
    \max \text{ degree} = \max(\max(\text{degree sequence real}), \max(\text{degree sequence rando})
    plt.xlim(0, max degree * 0.5)
    plt.savefig(filename)
    plt.show()
n instances=100
config graphs = []
for i in tgdm(range(n instances)):
    config graphs.append(configuration model(G, seed=i))
plot_degree_distribution(G, config_graphs, 'Configuration Model Degree Di
# Generate random graphs using Edge-Swapping Strategy
random graphs swap = edge swapping(G, instances=100)
plot degree distribution(G, random graphs swap, 'Edge-Swapping Degree Dis
               | 100/100 [00:28<00:00, 3.50it/s]
                         Configuration Model Degree Distribution
                                                                  Original Graph
                                                                  Random Graph
  70
  60
  50
Frequency
  40
  30
  20
  10
  0
                                                        200
                                           150
                                                                     250
                                      Degree
```

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Generating Random graph through Edge Swapping...



Q1

MORE DETAILED ANALYSIS

```
In [1]:
        import networkx as nx
        import numpy as np
        import matplotlib.pyplot as plt
        import time
        from collections import Counter
        import pandas as pd
        import seaborn as sns
        from tqdm import tqdm
        import warnings
        def generate_config_model(G, seed=None):
            Generate a random graph using the configuration model,
            preserving the in-degree and out-degree sequences.
            if seed is not None:
                np.random.seed(seed)
            in_degrees = [d for _, d in G.in_degree()]
            out_degrees = [d for _, d in G.out_degree()]
            # Generate random graph using configuration model
            R = nx.directed_configuration_model(in_degrees, out_degrees, seed=see
            # Remove parallel edges and self-loops
            R = nx.DiGraph(R)
            R.remove edges from(nx.selfloop edges(R))
            return R
        def generate_edge_swap_model(G, n_swaps=None, seed=None):
```

```
Generate a random graph using the edge-swapping strategy,
    preserving the exact in-degree and out-degree of each node.
    if seed is not None:
        np.random.seed(seed)
    # Create a copy of the original graph
    R = G.copy()
    # Set number of swaps if not specified
    if n swaps is None:
        n \text{ swaps} = 2 * R.number of edges()
    # Perform edge swaps
        nx.algorithms.swap.directed edge swap(
            R, nswap=n swaps, max tries=3*n swaps, seed=seed
    except nx.NetworkXError as e:
        print(f"Warning: Edge swap incomplete - {e}")
    return R
def get_degree_distribution(G):
    Get in-degree and out-degree distributions as dictionaries.
    in degree dist = Counter(dict(G.in degree()).values())
    out degree dist = Counter(dict(G.out degree()).values())
    total degree dist = Counter(dict(G.degree()).values())
    return {
        'in_degree': in_degree_dist,
        'out degree': out degree dist,
        'total degree': total degree dist
    }
def average_degree_distributions(graph_list):
    Average degree distributions across multiple graphs.
    avg_in = Counter()
    avg_out = Counter()
    avg_total = Counter()
    # Collect all degrees that appear in any graph
    all in degrees = set()
    all out degrees = set()
    all_total_degrees = set()
    for G in graph_list:
        dist = get_degree_distribution(G)
        for degree in dist['in degree']:
            all in degrees.add(degree)
        for degree in dist['out degree']:
            all out degrees.add(degree)
        for degree in dist['total_degree']:
            all_total_degrees.add(degree)
```

```
# Initialize counters with zeros for all degrees
    for degree in all in degrees:
        avg in[degree] = 0
    for degree in all out degrees:
        avg out[degree] = 0
    for degree in all total degrees:
        avg total[degree] = 0
    # Sum up counts for each degree
    for G in graph list:
        dist = get degree distribution(G)
        for degree, count in dist['in degree'].items():
            avg_in[degree] += count
        for degree, count in dist['out degree'].items():
            avg out[degree] += count
        for degree, count in dist['total degree'].items():
            avg total[degree] += count
    # Divide by number of graphs to get average
    n = len(graph list)
    for degree in avg in:
        avg in[degree] /= n
    for degree in avg out:
        avg out[degree] /= n
    for degree in avg total:
        avg total[degree] /= n
    return {
        'in degree': avg in,
        'out degree': avg out,
        'total degree': avg total
    }
def plot degree distributions(original dist, config dist, edge swap dist)
    Plot degree distributions for original graph and random graph models.
    # Set up figure with 3 subplots
    fig, axes = plt.subplots(1, 3, figsize=(18, 6))
    # Define degree types and their respective labels
    degree_types = ['in_degree', 'out_degree', 'total_degree']
    titles = ['In-Degree Distribution', 'Out-Degree Distribution', 'Total
    # For log-log plots
    for i, degree type in enumerate(degree types):
        ax = axes[i]
        # Convert data to dataframe for easier plotting
        data = []
        # Original graph
        for degree, count in sorted(original dist[degree type].items()):
            data.append({'Degree': degree, 'Count': count, 'Model': 'Orig
        # Configuration model
        for degree, count in sorted(config_dist[degree_type].items()):
            data.append({'Degree': degree, 'Count': count, 'Model': 'Conf
```

```
# Edge-swap model
        for degree, count in sorted(edge swap dist[degree type].items()):
            data.append({'Degree': degree, 'Count': count, 'Model': 'Edge
        df = pd.DataFrame(data)
        # Log-log plot
        sns.scatterplot(x='Degree', y='Count', hue='Model', style='Model'
                      data=df, ax=ax, alpha=0.7)
        ax.set xscale('log')
        ax.set yscale('log')
        ax.set xlabel('Degree (log scale)')
        ax.set ylabel('Count (log scale)')
        ax.set title(titles[i])
        ax.legend(title='')
        ax.grid(True, which='both', linestyle='--', linewidth=0.5)
    plt.tight layout()
    plt.show()
    plt.savefig('degree distributions.png', dpi=300, bbox inches='tight')
    plt.close()
    # Also create a cumulative distribution function plot
    fig, axes = plt.subplots(1, 3, figsize=(18, 6))
    for i, degree type in enumerate(degree types):
        ax = axes[i]
        # Create dataframes for each model
        models = {
            'Original': original dist[degree type],
            'Configuration': config dist[degree type],
            'Edge-Swap': edge swap dist[degree type]
        }
        for model name, dist in models.items():
            # Sort degrees and create cumulative distribution
            degrees = sorted(dist.keys())
            counts = [dist[d] for d in degrees]
            cum counts = np.cumsum(counts) / sum(counts)
            # Plot CDF
            ax.plot(degrees, 1 - cum counts, label=model name, marker='o'
        ax.set_xscale('log')
        ax.set yscale('log')
        ax.set xlabel('Degree (log scale)')
        ax.set_ylabel('P(X > x) (log scale)')
        ax.set title(f'CCDF of {titles[i]}')
        ax.legend()
        ax.grid(True, which='both', linestyle='--', linewidth=0.5)
    plt.tight_layout()
    plt.show()
    plt.savefig('degree_ccdf.png', dpi=300, bbox_inches='tight')
    plt.close()
def generate_statistics(original_graph, config_graphs, edge_swap_graphs):
```

```
Generate statistics for the original graph and random models.
    # Original graph statistics
    orig stats = {
        'nodes': original graph.number of nodes(),
        'edges': original graph.number of edges(),
        'density': nx.density(original graph),
        'avg clustering': nx.average clustering(original graph.to undirec
        'scc count': len(list(nx.strongly connected components(original g
        'largest scc': len(max(nx.strongly connected components(original
    }
    # Function to average statistics across multiple graphs
    def avg stats(graph list):
        stats = {
            'nodes': np.mean([G.number_of_nodes() for G in graph_list]),
            'edges': np.mean([G.number of edges() for G in graph list]),
            'density': np.mean([nx.density(G) for G in graph list]),
            'avg clustering': np.mean([nx.average clustering(G.to undired
            'scc count': np.mean([len(list(nx.strongly connected componen
            'largest scc': np.mean([len(max(nx.strongly connected compone
        }
        return stats
    # Calculate statistics for random models
    config_stats = avg_stats(config graphs)
    edge swap stats = avg stats(edge swap graphs)
    # Combine into a dataframe
    stat names = ['Nodes', 'Edges', 'Density', 'Avg. Clustering', 'SCC Co
    stat values = list(orig stats.values())
    config values = list(config stats.values())
    edge swap values = list(edge swap stats.values())
    df = pd.DataFrame({
        'Statistic': stat_names,
        'Original': stat values,
        'Configuration Model': config_values,
        'Edge-Swap Model': edge_swap_values
    })
    return df
start time = time.time()
original_graph = nx.read_edgelist('email-Eu-core.txt', create_using=nx.Di
# Number of random graph instances to generate
n instances = 100
# Generate random graphs using configuration model
print(f"Generating {n_instances} instances using Configuration Model...")
config graphs = []
for i in tqdm(range(n instances)):
    config graphs.append(generate config model(original graph, seed=i))
# Generate random graphs using edge-swapping
print(f"Generating {n_instances} instances using Edge-Swapping...")
edge_swap_graphs = []
for i in tqdm(range(n instances)):
```

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```
edge swap graphs.append(generate edge swap model(original graph, seed
# Get original degree distribution
original dist = get degree distribution(original graph)
# Average degree distributions for random models
config dist = average degree distributions(config graphs)
edge swap dist = average degree distributions(edge swap graphs)
# Plot degree distributions
print("Plotting degree distributions...")
plot degree distributions(original dist, config dist, edge swap dist)
# Generate statistics
print("Generating statistics...")
stats_df = generate_statistics(original_graph, config_graphs, edge_swap_g
print("\nGraph Statistics:")
print(stats df)
# Save statistics to CSV
stats df.to csv('graph statistics.csv', index=False)
# Report execution time
execution time = time.time() - start time
print(f"\nExecution time: {execution_time:.2f} seconds")
Generating 100 instances using Configuration Model...
              | 100/100 [00:21<00:00, 4.65it/s]
Generating 100 instances using Edge-Swapping...
             | 100/100 [02:25<00:00, 1.45s/it]
Plotting degree distributions...
        CCDF of In-Degree Distribution
                                  CCDF of Out-Degree Distribution
                                                            CCDF of Total Degree Distribution
scale)
                                                    (el 10
```

Generating statistics...

Graph Statistics:

	Statistic	Original	Configuration Model	Edge-Swap Model
0	Nodes	1005.000000	1005.000000	1005.000000
1	Edges	25571.000000	23849.750000	25571.000000
2	Density	0.025342	0.023637	0.025342
3	Avg. Clustering	0.399355	0.190093	0.229554
4	SCC Count	203.000000	153.770000	204.430000
5	Largest SCC Size	803.000000	852.230000	801.570000

Execution time: 293.36 seconds