Bhuvi Ghosh
60009210191

SNA Experiment-4

```
import numpy as np
import matplotlib.pyplot as plt
import math
from scipy.stats import expon
```

Generate Barabasi - Albert Network

In [2]:

```
# Returns an Barabasi-Albert network graph in an adjacency matrix format.
def BarabasiAlbert (m = 4, N_initial = 4, N = 100):
    if(m > N_initial):
        return

    adj_matrix = np.zeros((N_initial,N_initial))

    for i in range(N - N_initial):
        neighbours = choose_neighbour(m, adj_matrix)
        adj_matrix = add_node(adj_matrix)
        for k in range(len(adj_matrix)):
            if k in neighbours:
                adj_matrix[i][k] = 1
                adj_matrix[k][i] = 1
    return adj_matrix
```

In [3]:

```
# Generates the Probability of each node in the for of cumulative probility
def generate_cumulative_probability(adj_matrix):
    e = adj_matrix.sum()
    N = len(adj_matrix)
    probability = []

    if e < 1:
        probability = [(1.0/N) ]*N
        prev = 0
        for i,j in enumerate(probability):
            probability[i] = probability[i] + prev
            prev = probability[i]

    else:
        for i in range(N):
            degree = adj_matrix[i].sum()
            P_i = degree / (2*e)

            if i > 0:
                P_i += probability[i-1]

            probability.append(P_i)

    return probability
```

In [4]:

```
# Chooses m number of new neighbours for the new node.
# Based on the probabilities of each node and a random number generated in
the range (0,1) based on gaussian probability
```

```
def choose_neighbour(m, adj_matrix):
    probability = generate_cumulative_probability(adj_matrix)
    neighbours = []

    e = 0
    while(e < m):
        random = np.random.random_sample()
        index = -1
        if random <= probability[0]:
            index = 0

        else:
            for j in range(1, len(probability)):
                if random > probability[j-1] and random <= probability[j]:
                    index = j

        if index not in neighbours:
            neighbours.append(index)
            e += 1
    return neighbours
```

In [5]:

```
# Adds a new column and row to the adjacency matrix
def add_node(adj_matrix):
    x = np.zeros((1, len(adj_matrix)))
    y = np.zeros((1 + len(adj_matrix), 1))
    adj_matrix = np.hstack((np.vstack((adj_matrix, x)), y))
    return adj_matrix
```

Degree Distribution

In [6]:

```
graph = BarabasiAlbert()
degree_distribution = graph.sum(axis = 1)
```

In [18]:

```
fig , ax1 = plt.subplots(1, figsize = (9,6))
ax1.hist(degree_distribution, density = True, bins = 'auto', )
ax1.set_ylabel('Degree')
ax1.set_xlabel('Number of Nodes')
ax1.set_title('Degree Distrbution of Barabasi Albert Graph',
fontweight='bold')
fig.show()
```

Exponential Distribution fitting

In [8]:

```
# The parameter lambda is calcualted according the the MLE equation derived
in report
l = degree_distribution.sum()/len(degree_distribution)

# Exponential distribution fitting using expon package
loc, scale_fit = expon.fit(degree_distribution, floc=0)
```

```
l , scale_fit
x = np.linspace(expon.ppf(0.01, scale = scale_fit ), expon.ppf(0.99, scale =
scale_fit), 100)
```

In [17]:

```
fig , ax1 = plt.subplots(1, figsize = (9,8))
ax1.hist(degree_distribution, density = True, bins = 'auto', )
ax1.set_ylabel('Degree')
ax1.set_xlabel('Number of Nodes')
ax1.set_title('Degree Distrbution of Barabasi Albert Graph',
fontweight='bold')
ax1.plot(x, expon.pdf(x, scale = scale_fit), label = 'Exponential Fit')
ax1.text(95,0.6,'Lambda = %f'%(scale_fit))
ax1.legend()
fig.show()
```

Linear Least Square Fitting of Log-Log distribution

In [10]:

```
y = expon.pdf(x, scale = scale_fit)
xlog = np.log(x)
ylog = np.log(y)

A = np.vstack((xlog, np.ones(len(xlog))))
A = np.transpose(A)

log_C, log_gamma = np.linalg.lstsq(A, y, rcond=None)[0]
```

In [11]:

```
plt.figure()
plt.title(" Original Distribution vs Least Square Fit", fontweight ='bold')
plt.plot(xlog, ylog, '+', label = 'Original data')
plt.plot(xlog, log_C*xlog + log_gamma, color ='r', label = 'Least Squares
linear fit')
plt.ylabel("log p ")
plt.xlabel('log k')
plt.legend()
plt.show()
```

Power Law Fitting

In [16]:

```
import powerlaw
results = powerlaw.Fit(degree_distribution)
```

Scale-free network:

```
[ ] import numpy as np
    import matplotlib.pyplot as plt
    from scipy.stats import expon
    import powerlaw
```

```
def BarabasiAlbert(m = 4, N_initial = 4, N = 100):
    if m > N_initial:
        return None
    adj_matrix = np.zeros((N_initial, N_initial))

    for i in range(N - N_initial):
      neighbours = choose_neighbour(m, adj_matrix)
      adj_matrix = add_node(adj_matrix)

      for k in range(len(adj_matrix)):
            if k in neighbours:
                adj_matrix[i][k] = 1
                adj_matrix[k][i] = 1
    return adj_matrix
```

```
[ ] def generate_cumulative_probability(adj_matrix):
      e = adj_matrix.sum()
      N = len(adj_matrix)
      probability = []
      if e < 1:
            probability = [(1.0 / N)] * N
            prev = 0
            for i, j in enumerate(probability):
                probability[i] = probability[i] + prev
                prev = probability[i]
      else:
            for i in range(N):
                degree = adj_matrix[i].sum()  # Degree of the node
                P_i = degree / (2 * e)  # Probability of a node being selecte
                if i > 0:
                    P_i += probability[i - 1]
                probability.append(P_i)

      return probability
```

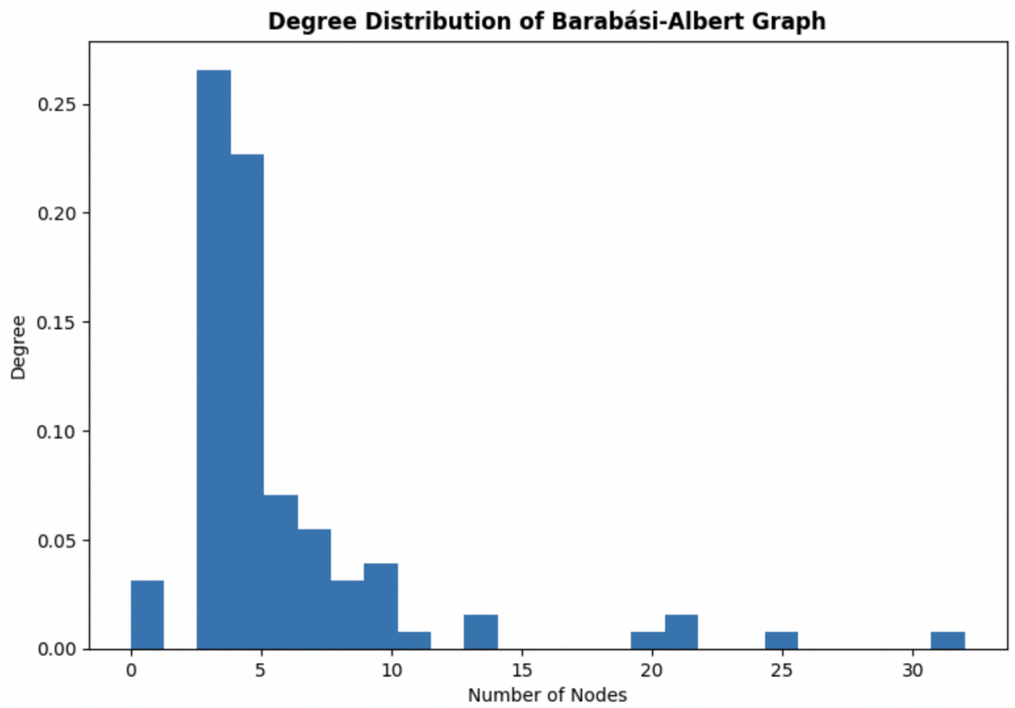
```
[ ] def choose_neighbour(m, adj_matrix):
        probability = generate_cumulative_probability(adj_matrix)
        neighbours = []
        e = 0

        while e < m:
            random = np.random.random_sample()  # Generate a random number between 0 and 1
            index = -1
            if random <= probability[0]:
                index = 0
            else:
                for j in range(1, len(probability)):
                    if random > probability[j - 1] and random <= probability[j]:
                        index = j

            if index not in neighbours:
                neighbours.append(index)
                e += 1

        return neighbours
```

```
[ ] def add_node(adj_matrix):
        x = np.zeros((1, len(adj_matrix)))
        y = np.zeros((1 + len(adj_matrix), 1))
        adj_matrix = np.hstack((np.vstack((adj_matrix, x)), y))  # Expand matrix
        return adj_matrix
```

```
[ ] graph = BarabasiAlbert(m=4, N_initial=4, N=100)
```

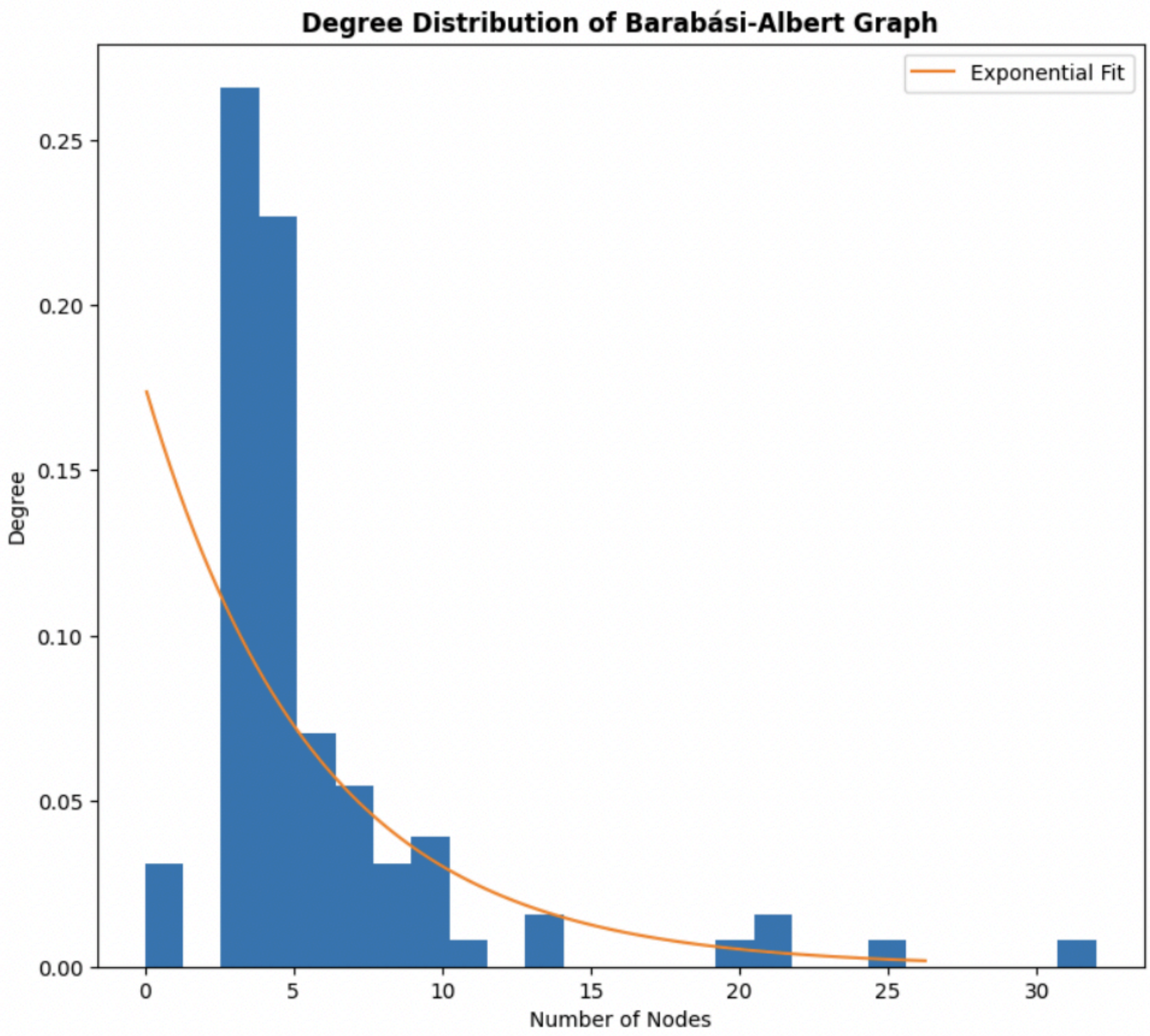
```
[ ] degree_distribution = graph.sum(axis=1)
```

```
fig, ax1 = plt.subplots(1, figsize=(9, 6))
ax1.hist(degree_distribution, density=True, bins='auto')
ax1.set_ylabel('Degree')
ax1.set_xlabel('Number of Nodes')
ax1.set_title('Degree Distribution of Barabási-Albert Graph', fontweight='bold')
plt.show()
```



```
[ ] l = degree_distribution.sum() / len(degree_distribution)
    loc, scale_fit = expon.fit(degree_distribution, floc=0)
```

```
x = np.linspace(expon.ppf(0.01, scale=scale_fit), expon.ppf(0.99, scale=scale_fit), 100)
fig, ax1 = plt.subplots(1, figsize=(9, 8))
ax1.hist(degree_distribution, density=True, bins='auto')
ax1.set_ylabel('Degree')
ax1.set_xlabel('Number of Nodes')
ax1.set_title('Degree Distribution of Barabási-Albert Graph', fontweight='bold')
ax1.plot(x, expon.pdf(x, scale=scale_fit), label='Exponential Fit')
ax1.text(95, 0.6, 'Lambda = %f' % (scale_fit))
ax1.legend()
plt.show()
```



```
[ ] results = powerlaw.Fit(degree_distribution)
    print(f"Power law alpha: {results.power_law.alpha}")
    print(f"Power law xmin: {results.power_law.xmin}")
```

```
Calculating best minimal value for power law fit
Power law alpha: 3.2298377817147332
Power law xmin: 5.0
Values less than or equal to 0 in data. Throwing out 0 or negative values
```

```
fig, ax = plt.subplots(1, figsize=(9, 6))
results.plot_pdf(label='Empirical Data')
results.power_law.plot_pdf(color='r', linestyle='--', label='Power Law Fit')
ax.set_xlabel('Degree')
ax.set_ylabel('Probability Density')
ax.legend()
plt.show()
```