12/4/24, 10:19 PM A6.ipynb - Colab

Response: Summary and Observation

I used a 1% random sample of values for most of the analysis. Out of the six metrics, K-Core Centrality and PageRank are the most interesting. The K-Core Centrality histogram shows that most nodes are in the outer layers of the network, with only a small number deeply embedded in the core. This means the network relies on a few highly connected nodes to stay strong. PageRank helps pinpoint the most influential nodes, especially in the high-replies dataset, where a small number of nodes dominate.

Degree Centrality and Betweenness Centrality are helpful but harder to interpret visually because the graphs have overlapping labels. Degree Centrality shows the nodes with the most connections, while Betweenness Centrality highlights the ones that act as bridges connecting different parts of the network. Closeness Centrality shows how easily nodes can reach others in the network, and Percolation Centrality reveals that most nodes don't have much impact on the overall structure.

In summary, the analysis shows that the network depends on a few key nodes for strength and influence, while most nodes play a less significant role.

```
Start coding or generate with AI.
from google.colab import drive
drive.mount('/content/drive')
  → Mounted at /content/drive
import pandas as pd
import networkx as nx
import numpy as np
%matplotlib inline
!ls "/content/drive/My Drive/Colab Notebooks/cs131"
          cleaned_combined_AdjList.tsv
                                                                                                                                                    {\tt replies\_nobots\_uniq\_lowinfluence.txt}
                                                                                                                                                    retweets highinfluence count.txt
             combined_AdjList.tsv
            Copy_of_twitter_high_and_low_analysis_2024-1.ipynb retweets_lowinfluence_count.txt highinfl_AdjList.tsv retweets_nobots uniq highinfluence
                                                                                                                                                    retweets_nobots_uniq_highinfluence.NONOUSER.txt
             lowinfl_AdjList.tsv
                                                                                                                                                    retweets_nobots_uniq_highinfluence.txt
             replies_highinfluence_count.txt
                                                                                                                                                    retweets_nobots_uniq_lowinfluence.NONOUSER.txt
             replies_lowinfluence_count.txt
                                                                                                                                                    retweets_nobots_uniq_lowinfluence.txt
             replies_nobots_uniq_highinfluence.txt
#DEFINE COLUMN
column_names=['A','B']
highinfl_df = pd.read_csv('/content/drive/My Drive/Colab Notebooks/cs131/retweets_nobots_uniq_highinfluence.txt',
                                                                   sep=r'\s+', names=column names, engine='python')
lowinfl_df = pd.read_csv('/content/drive/My Drive/Colab Notebooks/cs131/retweets_nobots_uniq_lowinfluence.txt',
                                                                 sep=r'\s+', names=column_names, engine='python')
# Ensure columns 'A' and 'B' are strings
highinfl_df['A'] = highinfl_df['A'].astype(str)
highinfl_df['B'] = highinfl_df['B'].astype(str)
lowinfl_df['A'] = lowinfl_df['A'].astype(str)
lowinfl_df['B'] = lowinfl_df['B'].astype(str)
# Clean each DataFrame by removing rows with 'UNKNOWNUSER' in columns A or B
\label{local_high_infl_df} \mbox{$highinfl_df['A'].str.contains(r'^UNKNOWNUSER\d+', na=False)]} \\
\label{limit} highinfl\_df = highinfl\_df[\ 'B'].str.contains(r'^UNKNOWNUSER\ 'd+', \ na=False)]
lowinfl_df = lowinfl_df[~lowinfl_df['A'].str.contains(r'^UNKNOWNUSER\d+', na=False)]
lowinfl_df = lowinfl_df[~lowinfl_df['B'].str.contains(r'^UNKNOWNUSER\d+', na=False)]
# Save the cleaned individual DataFrames
\label{linear_continuity} high in fluctor ('/content/drive/My \ Drive/Colab \ Notebooks/cs131/retweets_nobots\_uniq\_high influence.NONOUSER.txt', notebooks/cs131/retweets\_nobots\_uniq\_high influence.NONOUSER.txt', notebooks/cs131/retweets\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_no
                                                 sep='\t', index=False, header=False)
lowinf1\_df.to\_csv('/content/drive/My~Drive/Colab~Notebooks/cs131/retweets\_nobots\_uniq\_lowinf1uence.NONOUSER.txt', the state of the st
                                               sep='\t', index=False, header=False)
# Combine the cleaned DataFrames
combined_data = pd.concat([highinfl_df, lowinfl_df], ignore_index=True)
# Save the combined data
combined_data.to_csv('/content/drive/My Drive/Colab Notebooks/cs131/cleaned_combined_AdjList.tsv',
                                                      sep='\t', index=False)
print("Cleaning and saving completed successfully!")
  Transfer Cleaning and saving completed successfully!
# Define column names
column_names = ['A',
# Load the data
highinfl_df = pd.read_csv('/content/drive/My Drive/Colab Notebooks/cs131/replies_nobots_uniq_highinfluence.txt',
                                                                    sep=r'\s+', names=column_names, engine='python')
lowinf1_df = pd.read_csv('/content/drive/My Drive/Colab Notebooks/cs131/replies_nobots_uniq_lowinfluence.txt',
                                                                sep=r'\s+', names=column_names, engine='python')
# Ensure columns 'A' and 'B' are strings
highinfl_df['A'] = highinfl_df['A'].astype(str)
highinfl_df['B'] = highinfl_df['B'].astype(str)
lowinfl_df['A'] = lowinfl_df['A'].astype(str)
lowinfl_df['B'] = lowinfl_df['B'].astype(str)
# Clean each DataFrame by removing rows with 'UNKNOWNUSER' in columns A or B
\label{local_high_infl_df} \mbox{$highinfl_df['A'].str.contains(r'^UNKNOWNUSER\d+', na=False)]} \\
highinfl_df = highinfl_df[~highinfl_df['B'].str.contains(r'^UNKNOWNUSER\d+', na=False)]
lowinfl_df = lowinfl_df[~lowinfl_df['A'].str.contains(r'^UNKNOWNUSER\d+', na=False)]
lowinfl\_df = lowinfl\_df[`B'].str.contains(r'^UNKNOWNUSER\d+', na=False)]
# Save the cleaned individual DataFrames
\label{limit} high infl\_df.to\_csv('/content/drive/My\ Drive/Colab\ Notebooks/cs131/replies\_nobots\_uniq\_high influence.NONOUSER.txt', and the sum of the property of the prop
                                                 sep='\t', index=False, header=False)
lowinfl\_df.to\_csv('\underline{/content/drive/My\ Drive/Colab}\ Notebooks/cs131/replies\_nobots\_uniq\_lowinfluence.NONOUSER.txt', \\
                                               sep='\t', index=False, header=False)
```

12/4/24, 10:19 PM A6.ipynb - Colab

```
# Combine the cleaned DataFrames
combined_data = pd.concat([highinfl_df, lowinfl_df], ignore_index=True)
# Save the combined data
combined\_data.to\_csv('\underline{/content/drive/My\_Drive/Colab}\_Notebooks/cs131/cleaned\_replies\_combined\_AdjList.tsv',
                     sep='\t', index=False)
print("Cleaning and saving completed successfully!")
→ Cleaning and saving completed successfully!
highinfl_df.head()
₹
                                      В
                                          Ш
      0 100256670
                              105327432
      1 100256670 1058038885765255175
      2 100256670
                             1064545651
      3 100256670
                              109071031
      4 100256670 1120698997327294464
 Next steps: Generate code with highinfl_df
                                               View recommended plots
                                                                              New interactive sheet
#print the number of columns in the data frame
num_rows,num_cols=combined_data.shape
print('Number of rows:',num_rows)
print('Number of column:',num_cols)
Number of rows: 88718
     Number of column: 2
#How many number of rows and columns for retweeet
num_rows,num_cols=highinfl_df.shape
print('Number of rows:',num_rows)
print('Number of column:',num_cols)
Number of rows: 42426
     Number of column: 2
#How many number of rows and columns for retweeet
\verb|num_rows,num_cols=lowinfl_df.shape|\\
print('Number of rows:',num_rows)
print('Number of column:',num_cols)
Number of rows: 46292
     Number of column: 2
highinfl_df['B']=highinfl_df['B'].astype(int)
lowinfl_df['B']=lowinfl_df['B'].astype(int)
#view the first few rows and columns for high for retweet
highinfl_df.head()
\overline{\Rightarrow}
                                          П
                                      В
      0 100256670
                              105327432
      1 100256670 1058038885765255175
      2 100256670
                             1064545651
                              109071031
      3 100256670
      4 100256670 1120698997327294464
 Next steps: Generate code with highinfl_df
                                               View recommended plots
                                                                              New interactive sheet
#view the last few rows and columns for high for retweet
highinfl_df.tail()
\overline{\mathbf{T}}
      43386 997528560482050048 718863328060289025
      43387 997528560482050048
                                          778714123
      43388 997528560482050048 872947287584120832
      43389 997528560482050048 873135988440223745
      43390 997528560482050048 916972497240719361
#view the first few rows and columns
lowinfl_df.head()
\overline{\mathbf{T}}
      0 100256670 1063468160127385601
      1 100256670 1070083706822438912
      2 100256670
                             1075392210
      3 100256670 1082048954269818880
      4 100256670 1171150024983470080
#view the last few rows and columns for low for retweet
lowinfl_df.tail()
\overline{z}
                              Α
                                                  В
      52512 997528560482050048 967853319166230529
      52513 997528560482050048 986380469959909376
      52514 997528560482050048 987148809561141248
      52515 997528560482050048 993278238037299200
      52516 997528560482050048 998693754981703682
```

```
#view the first few rows and columns
combined_data.head()
```

```
        A
        B

        0
        100256670
        105327432

        1
        100256670
        1058038885765255175

        2
        100256670
        1064545651

        3
        100256670
        109071031

        4
        100256670
        1120698997327294464
```

#view the last few rows and columns
combined_data.tail()

```
        A
        B

        88713
        997528560482050048
        967853319166230529

        88714
        997528560482050048
        986380469959909376

        88715
        997528560482050048
        987148809561141248

        88716
        997528560482050048
        993278238037299200

        88717
        997528560482050048
        998693754981703682
```

highinfl_df['B']=highinfl_df['B'].astype(int)
highinfl_df['A']=highinfl_df['A'].astype(int)
lowinfl_df['B']=lowinfl_df['B'].astype(int)
lowinfl_df['A']=lowinfl_df['A'].astype(int)
combined_data['A']=combined_data['A'].astype(int)
combined_data['B']=combined_data['B'].astype(int)

#view the name of columns
highinfl_df.columns
lowinfl_df.columns
combined_data.columns

→ Index(['A', 'B'], dtype='object')

#view the information about the combined for retweet
print(combined_data.info())

```
cclass 'pandas.core.frame.DataFrame'>
RangeIndex: 88718 entries, 0 to 88717
Data columns (total 2 columns):
# Column Non-Null Count Dtype
0 A 88718 non-null int64
1 B 88718 non-null int64
dtypes: int64(2)
memory usage: 1.4 MB
None
```

#view the information about the low infl for retweet
print(lowinfl_df.info())

```
<p
```

#check of ther are in combined data any mising value
print(combined_data.isnull().sum())

A 0 B 0 dtype: int64

#check of there are any missing value in highinfl value
print(highinfl_df.isnull().sum())

A 0 B 0 dtype: int64

#check of there are any missing value in lowinl value
print(lowinfl_df.isnull().sum())

→ A 0 B 0

#summarize the data set by calculating some basic statistcs of combined:
print(combined_data.describe().astype(int).to_string())

```
\overline{\Rightarrow}
    count
                          88718
                                                88718
            380248972446081856 394877655766910080
    mean
            546029463600453824 561304233132552256
    min
                      14362766
                                           125143408
    25%
                     148365388
                                          1223575264
    50%
                     1164487040
            939679358536507392 959342442823694336
    75%
           1513724522792636416 1519721637494595584
    max
```

#summarize the data set by calculating some basic statistcs of highinfl for retweet:
print(highinfl_df.describe().astype(int).to_string())

$\overline{\Rightarrow}$		Α	В
	count	42426	42426
	mean	384745755614000128	334506100817180352
	std	542731639062526656	528292801808115008
	min	14362766	985
	25%	192374137	88869834
	50%	1164487040	731943463
	75%	939679358536507392	832524310199824384
	max	1506670136790589440	1516654448252428288

12/4/24 10:20 PM

```
A6.ipynb - Colab
#summarize the data set by calculating some basic statistcs of lowinfl for retweet:
print(lowinfl_df.describe().astype(int).to_string())
                          46292
                                                46292
     count
                                   450207379915731392
             376127730704914944
     mean
     std
             549007993063470336
                                   584493437133760896
                       14362766
     min
     25%
                      135624348
                                            171022949
     50%
                     1343565854
                                           2191380827
             950215424981028864 1071977963562825728
     75%
     max
            1513724522792636416 1519721637494595584
import pandas as pd
import matplotlib.pyplot as plt
highinfl_df = pd.read_csv('/content/drive/My Drive/Colab Notebooks/cs131/retweets_nobots_uniq_highinfluence.NONOUSER.txt', sep='\t', names=column_names)
df = pd.read_csv('/content/drive/My Drive/Colab Notebooks/cs131/retweets_nobots_uniq_lowinfluence.NONOUSER.txt', sep='\t', names=column_names)
print(df.columns)
Index(['A', 'B'], dtype='object')

    Degree centrality

#Load the high infl adj list file into a networkx a graph
G = nx.read_edgelist('/content/drive/My Drive/Colab Notebooks/cs131/retweets_nobots_uniq_highinfluence.NONOUSER.txt',delimiter='\t')
#calculate the degree centratlity for each node in the graph
degree_centrality=nx.degree_centrality(G)
#find the node with the highest degree centrality
max_node=max(degree_centrality,key=degree_centrality.get)
max_degree_centrality=degree_centrality[max_node]
#print the highest degree centeraltiy for each node in the graph
print(f'node with the highest degree centrality is {max_node}with a centrality value of{degree_centrality[max_node]:.3f}.')
node with the highest degree centrality is 42769304with a centrality value of0.089.
#print the degree centraltiy for each node in the graph
for node, centrality in degree_centrality.items():
    print(f'Node{node}has degree centrality{centrality:.3f}.')
    Streaming output truncated to the last 5000 lines.
     Node1040160799208161280has degree centrality0.001.
     Node1042307696has degree centrality0.002.
     Node1065677660880338944has degree centrality0.001.
     Node1100266332283559936has degree centrality0.000.
     Node1123996182has degree centrality0.002.
     Node1370616208928747520has degree centrality0.001.
     Node1497193035028963365has degree centrality0.001.
     Node1542862735has degree centrality0.001.
     Node16442365has degree centrality0.000.
     Node203307838has degree centrality0.000.
     Node22720074has degree centrality0.000.
     Node229195516has degree centrality0.001.
     Node2315512764has degree centrality0.001.
     Node256159524has degree centrality0.001.
     Node2600066592has degree centrality0.001.
     Node3044584264has degree centrality0.001.
     Node311340314has degree centrality0.001.
     Node368240745has degree centrality0.002.
     Node46817943has degree centrality0.002.
     Node4786238905has degree centrality0.000.
     Node5900252has degree centrality0.001.
     Node717446052698304513has degree centrality0.001.
     Node82097756has degree centrality0.001.
Node848691418591891456has degree centrality0.001.
     Node949681897has degree centrality0.001.
     Node1154228711731990528has degree centrality0.002.
     Node1648351has degree centrality0.001.
     Node1155192156has degree centrality0.042.
     Node1008340728114601984has degree centrality0.001.
     Node 1080188052365029376 has \ degree \ centrality \textbf{0.001}.
     Node110893874has degree centrality0.001.
     Node1120952978393849856has degree centrality0.001.
     Node 1121967352181030912 has \ degree \ centrality \textbf{0.001}.
     Node113030544has degree centrality0.000.
     Node1134152253353447424has degree centrality0.001.
     Node1155192538535550976has degree centrality0.002.
     Node1175947712124063745has degree centrality0.001.
     Node1221554431541633024has degree centrality0.001.
     Node1243976208154529795has degree centrality0.001.
     Node1244795359097958401has degree centrality0.002.
     Node1317940454084825088has degree centrality0.001.
     Node1318376979930914816has degree centrality0.000.
     Node1321505685813760000has degree centrality0.001.
     Node1331107444416770048has degree centrality0.001.
     Node1340885244577263616has degree centrality0.000.
     Node134758540has degree centrality0.001.
     Node1348930324047286272has degree centrality0.001.
     Node1378022598752223235has degree centrality0.000.
     Node1409613542068613121has degree centrality0.001.
     Node1410700164067647495has degree centrality0.001.
     {\tt Node1425867981112893448} has \ {\tt degree} \ {\tt centrality0.000}.
     Node1441585487316062223has degree centrality0.001.
```

#plot a histo gram of the degree centrality values plt.hist(list(degree_centrality.values()),bins=5) plt.xlabel('Degree centrality',fontsize=24) plt.xticks(range(10,100,10)) plt.axvline(x=degree_centrality[max_node],color='red') plt.ylabel('Number of nodes',fontsize=24) plt.gca().get_yaxis().get_major_locator().set_params(integer=True) #plt.yticks([1,2,3,4])

degree_centrality={k:int(v*1000)for k,v in degree_centrality.items()}

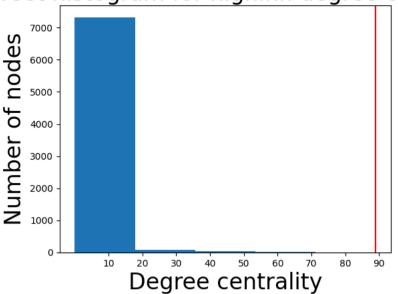
Node1452626837004173313has degree centrality0.000. Node1465353868624207873has degree centrality0.001. Node1469151855074762755has degree centrality0.000. Node1472371170758512653has degree centrality0.000. Node1479127693077721092has degree centrality0.001.

#convert the centrality values to integers

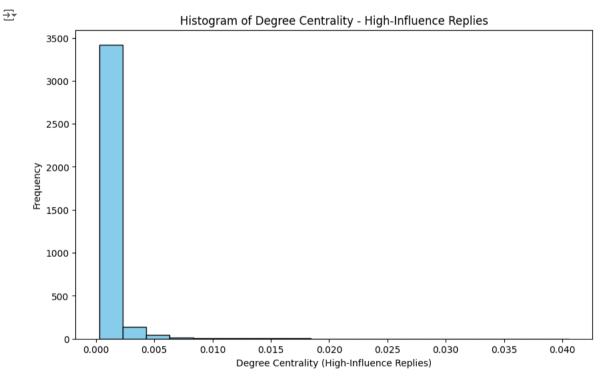
12/4/24, 10:20 PM A6.ipynb - Colab

 $\label{lem:plt.title} $$ plt.title('retweet histogram for highinfl degree centrality',fontsize=24) $$ plt.show() $$$

retweet histogram for highinfl degree centrality



```
import networkx as nx
import matplotlib.pyplot as plt
import pandas as pd
# Load the cleaned high-influence replies adjacency list into a NetworkX graph
G_high = nx.read_edgelist(high_replies_file, delimiter='\t', create_using=nx.Graph())
# Calculate Degree Centrality
degree_centrality_high = nx.degree_centrality(G_high)
# Save Degree Centrality to a file
degree_centrality_df_high = pd.DataFrame(list(degree_centrality_high.items()), columns=['Node', 'Degree Centrality'])
degree_centrality_df_high.to_csv('/content/drive/My Drive/Colab Notebooks/cs131/degree_centrality_high_replies.tsv', sep='\t', index=False)
# Plot histogram for Degree Centrality
plt.figure(figsize=(10, 6))
plt.hist(degree_centrality_high.values(), bins=20, color='skyblue', edgecolor='black')
plt.xlabel('Degree Centrality (High-Influence Replies)')
plt.ylabel('Frequency')
plt.title('Histogram of Degree Centrality - High-Influence Replies')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True)
plt.show()
```



#Load the high infl adj list file into a networkx a graph
G= nx.read_edgelist('/content/drive/My Drive/Colab Notebooks/cs131/retweets_nobots_uniq_lowinfluence.NONOUSER.txt',delimiter='\t')

#calculate the degree centratlity for each node in the graph
degree_centrality=nx.degree_centrality(G)

#find the node with the highest degree centrality
max_node=max(degree_centrality,key=degree_centrality.get)
max_degree_centrality=degree_centrality[max_node]

print(f'node with the highest degree centrality is {max_node}with a centrality value of{degree_centrality[max_node]:.3f}.')

node with the highest degree centrality is 2189523500with a centrality value of0.022.

#print the degree centraltiy for each node in the graph
for node, centrality in degree_centrality.items():
 print(f'Node{node}has degree centrality{centrality:.3f}.')

Streaming output truncated to the last 5000 lines.

Node121594232has degree centrality0.000.

Node1216813913150500866has degree centrality0.000.

Node1221016504067592193has degree centrality0.000.

Node1221377785has degree centrality0.000.

Node1221878704743223209has degree centrality0.000.

Node1231878704743223296has degree centrality0.000.

Node1232653578055147522has degree centrality0.000.

Node123595986810232833has degree centrality0.000.

Node1241760253has degree centrality0.000.

Node1242142822532292608has degree centrality0.000.

Node1250047514021171201has degree centrality0.000.

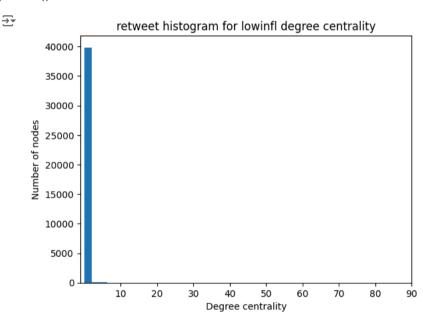
Node1251761794974015491has degree centrality0.000.

Node125362283has degree centrality0.000.

```
Node 1260946135797190656 has \ degree \ centrality \textbf{0.000}.
Node1280540497has degree centrality0.000.
Node1287118441007259649has degree centrality0.000.
Node128968687has degree centrality0.000.
Node129963753has degree centrality0.000.
Node1304589818has degree centrality0.000.
Node130555328has degree centrality0.000.
Node130640704has degree centrality0.000.
Node1308253814has degree centrality0.000.
Node1315972154517794822has degree centrality0.000.
Node 1316398228569546755 has \ degree \ centrality \textbf{0.000}.
Node 1323634389050339328 has \ degree \ centrality \textbf{0.000}.
Node 1324698582495203330 has \ degree \ centrality \textbf{0.000.}
Node1325265709has degree centrality0.000.
Node1326873186596777985has degree centrality0.000.
Node1328697528825618432has degree centrality0.000.
Node1328699022has degree centrality0.000.
Node1328788482353934340has degree centrality0.000.
Node1334814328084688896has degree centrality0.000.
Node1344651471858630656has degree centrality0.000.
Node 1345677728138334208 has \ degree \ centrality \textbf{0.000}.
Node1346268799has degree centrality0.000.
Node134793154has degree centrality0.000.
Node1355553109959962628has degree centrality0.000.
Node1355828513132187649has degree centrality0.000.
Node1360292790has degree centrality0.000.
Node1363174494299430914has degree centrality0.000.
Node1367853648has degree centrality0.000.
Node1377269138has degree centrality0.000.
Node 1378947769184976896 has \ degree \ centrality \textbf{0.000}.
Node1379292876has degree centrality0.000.
Node1379638549has degree centrality0.000.
Node1381715133706162176has degree centrality0.000.
Node138363206has degree centrality0.000.
Node139230276has degree centrality0.000.
Node1397240360338956292has degree centrality0.000.
Node1398234331135500292has degree centrality0.000.
Node1400580861150613506has degree centrality0.000.
Node1400783012has degree centrality0.000.
Node14048767has degree centrality0.000.
Node14275715has degree centrality0.000.
Node1430446644571607045has degree centrality0.000.
Node1433791346has degree centrality0.000.
Node1439338194has degree centralitv0.000.
```

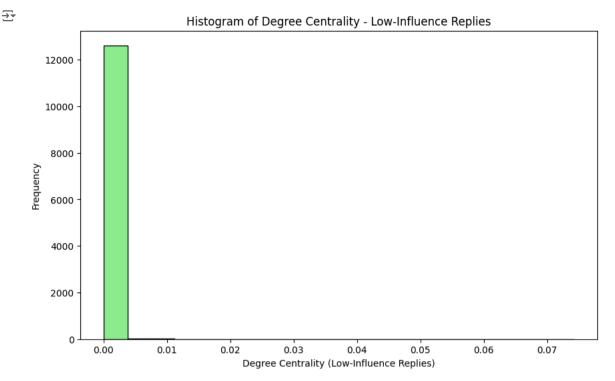
#convert the centrality values to integers
degree_centrality={k:int(v*1000)for k,v in degree_centrality.items()}

```
#plot a histo gram of the degree centrality values
plt.hist(list(degree_centrality.values()),bins=10)
plt.xlabel('Degree centrality')
plt.xticks(range(10,100,10))
#plt.xticks([0,10,20,30,40,50,60,70,80,90,100])
plt.ylabel('Number of nodes')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True)
#plt.yticks([1,2,3,4])
plt.title('retweet histogram for lowinfl degree centrality')
plt.show()
```



```
# Load the cleaned low-influence replies adjacency list into a NetworkX graph
low\_replies\_file = '\underline{/content/drive/My\ Drive/Colab}\ Notebooks/cs131/replies\_nobots\_uniq\_lowinfluence.NONOUSER.txt'
G_low = nx.read_edgelist(low_replies_file, delimiter='\t', create_using=nx.Graph())
# Calculate Degree Centrality
degree_centrality_low = nx.degree_centrality(G_low)
# Save Degree Centrality to a file
degree_centrality_df_low = pd.DataFrame(list(degree_centrality_low.items()), columns=['Node', 'Degree Centrality'])
\label{low_content_def} degree\_centrality\_df_low\_to\_csv(' \underline{/content/drive/My\ Drive/Colab}\ Notebooks/cs131/degree\_centrality\_low\_replies.tsv',\ sep='\t',\ index=False)
# Plot histogram for Degree Centrality
plt.figure(figsize=(10, 6))
plt.hist(degree_centrality_low.values(), bins=20, color='lightgreen', edgecolor='black')
plt.xlabel('Degree Centrality (Low-Influence Replies)')
plt.ylabel('Frequency')
plt.title('Histogram of Degree Centrality - Low-Influence Replies')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True)
plt.show()
```

12/4/24, 10:20 PM A6.ipynb - Colab



#Load the high infl adj list file into a networkx a graph
G= nx.read_edgelist('/content/drive/My Drive/Colab Notebooks/cs131/cleaned_combined_AdjList.tsv',delimiter='\t')

 $\label{prop:control} \mbox{\tt \#calculate the degree centrality for each node in the graph $\deg e_centrality=nx.degree_centrality(G)$}$

#find the node with the highest degree centrality
max_node=max(degree_centrality,key=degree_centrality.get)
max_degree_centrality=degree_centrality[max_node]

print(f'node with the highest degree centrality is {max_node}with a centrality value of{degree_centrality[max_node]:.3f}.')

node with the highest degree centrality is 42769304with a centrality value of0.030.

#print the degree centraltiy for each node in the graph
for node, centrality in degree_centrality.items():
 print(f'Node{node}has degree centrality{centrality:.3f}.')

→ Streaming output truncated to the last 5000 lines. Node1111094288467800064has degree centrality0.000. Node1151822814846029824has degree centrality0.000. Node1194244593170231296has degree centrality0.000. Node1213953152has degree centrality0.000. Node1307690532215435264has degree centrality0.000. Node1330349107has degree centrality0.000. Node1359952496140156933has degree centrality0.000. Node1364874243557752833has degree centrality0.000. $Node 1387674053389873152 has \ degree \ centrality \textbf{0.000}.$ Node1425101591313530886has degree centrality0.000. Node1425943814137651212has degree centrality0.000. Node1440635012has degree centrality0.000. Node1504202114129530881has degree centrality0.000. Node1512644840131026949has degree centrality0.000. Node1525234429has degree centrality0.000. Node166883389has degree centrality0.000. Node17092592has degree centrality0.000. Node19534496has degree centrality0.000. Node2316064569has degree centrality0.000. Node23294237has degree centrality0.000. Node2445637219has degree centrality0.000. Node263327246has degree centrality0.000. Node2795748238has degree centrality0.000. Node291521804has degree centrality0.000. Node302491448has degree centrality0.000. Node3060891761has degree centrality0.000. Node3128782139has degree centrality0.000. Node31503048has degree centrality0.000. Node33482561has degree centrality0.000. Node454696257has degree centrality0.000. Node4788937961has degree centrality0.000. Node48575074has degree centrality0.000. Node485860087has degree centrality0.000. Node833170111has degree centrality0.000. Node90996954has degree centrality0.000. Node975558929584279552has degree centrality0.000. $Node 984989302550552576 has \ degree \ centrality \textbf{0.000.}$ Node111400999has degree centrality0.000. Node1121789470171258880has degree centrality0.000. $Node 1274803192203579392 has \ degree \ centrality \textbf{0.000}.$ Node1296035989has degree centrality0.000. Node1319523522has degree centrality0.000. Node1326272512808857641has degree centrality0.000. Node1383377382824837130has degree centrality0.000. Node1403537423905169412has degree centrality0.000. Node1403713091972571136has degree centrality0.000. Node1447742440291504128has degree centrality0.000. Node1457894861311549444has degree centrality0.000. Node14730894has degree centrality0.000. Node177564016has degree centrality0.000. Node2301990517has degree centrality0.000. Node242694418has degree centrality0.000. Node2908170952has degree centrality0.000. Node394147536has degree centrality0.000. Node466864852has degree centrality0.000. Node4765364386has degree centrality0.000. Node4780832983has degree centrality0.000.

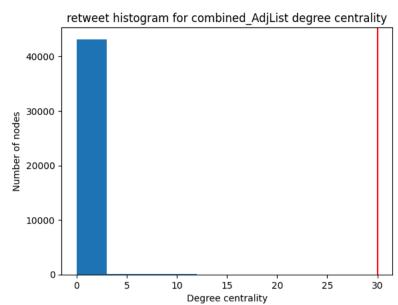
#convert the centrality values to integers
degree_centrality={k:int(v*1000)for k,v in degree_centrality.items()}

#plot a histo gram of the degree centrality values
plt.hist(list(degree_centrality.values()),bins=10)
plt.xlabel('Degree centrality')
plt.axvline(x=degree_centrality[max_node],color='red')
#plt.xticks(range(0,10,1))
#plt.xticks([0,10,20,30,40,50,60,70,80,90])
plt.ylabel('Number of nodes')
#plt.yticks([5,10,15,20,25,30,35])
plt.gca().get_yaxis().get_major_locator().set_params(integer=True)

12/4/24, 10:20 PM A6.ipynb - Colab

plt.title('retweet histogram for combined_AdjList degree centrality')
plt.show()

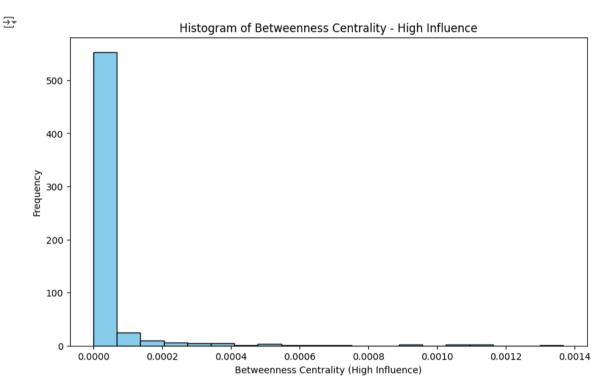
____*



Betweenness centrality

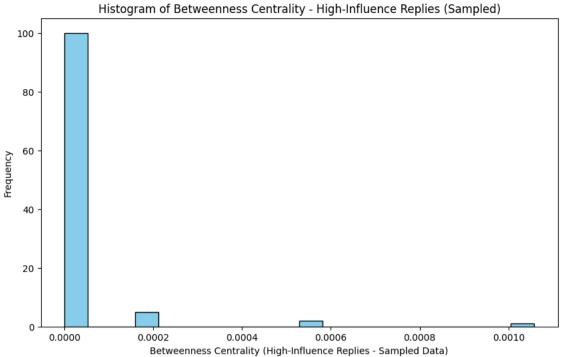
```
\# Create highinfl_df contains the adjacency data
\label{linear_fine_fine_fine_fine} high in fl_df. to \_csv('/content/drive/My \ Drive/Colab \ Notebooks/cs131/high in fl_AdjList.tsv', \ sep='\t', \ index=False) \\
# Create a 1% Random Sample from the Large File
import random
# Input and output file paths
input_file = '/content/drive/My Drive/Colab Notebooks/cs131/highinfl_AdjList.tsv'
output_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_highinfl_AdjList.tsv'
# Define sampling rate (1%)
sampling_rate = 0.01
# Create a random sample
with open(input_file, 'r') as infile, open(output_file, 'w') as outfile:
    for line in infile:
        if random.random() < sampling_rate: # Keep 1% of lines randomly</pre>
            outfile.write(line)
print(f"Random sample saved to: {output_file}")
3 Random sample saved to: /content/drive/My Drive/Colab Notebooks/cs131/sampled_highinfl_AdjList.tsv
# Load the Sampled File into a NetworkX Graph
import networkx as nx
import pandas as pd
# Load the sampled adjacency list
sampled_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_highinfl_AdjList.tsv'
G = nx.read_edgelist(sampled_file, delimiter='\t')
# Calculate betweenness centrality
centrality = nx.betweenness_centrality(G)
# Save centrality to a file
centrality\_df = pd.DataFrame(list(centrality.items()), columns=['Node', 'Betweenness Centrality'])
centrality_output = '/content/drive/My Drive/Colab Notebooks/cs131/betweenness_centrality_sampled.tsv'
centrality_df.to_csv(centrality_output, sep='\t', index=False)
print(f"Betweenness\ centrality\ calculated\ and\ saved\ to:\ \{centrality\_output\}")
Estweenness centrality calculated and saved to: /content/drive/My Drive/Colab Notebooks/cs131/betweenness_centrality_sampled.tsv
#print the betweenness centrality of each node
for node, centrality_score in centrality.items():
    print(f'Node{node}:{centrality_score}')
\overline{\Rightarrow}
```

```
Node967871677399994368:0.0
     Node189868631:0.0
     Node968008274003005440:0.0
     Node1509220917955682307:0.0
     Node971082899381305344:1.738344400792685e-05
     Node1507338108:0.0
     Node187796215:0.0
     Node763010018:0.0
     Node977710998:0.0
     Node3156867768:0.0
     Node981310761862606848:0.00012168410805548795
     Node1017551740319797248:0.0
     Node14764240:0.0
     Node981436419087523840:0.0
     Node255812611:0.0
     Node982511286:0.0
     Node473482276:0.0
     Node989200133215617024:0.0
     Node1059675376111312897:0.0
    Node997262774:0.0
Node1187055258712924162:0.0
import matplotlib.pyplot as plt
# Plot histogram for betweenness centrality
plt.figure(figsize=(10, 6))
plt.hist(centrality.values(), bins=20, color='skyblue', edgecolor='black')
plt.xlabel('Betweenness Centrality (High Influence)')
plt.ylabel('Frequency')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True) # Ensure y-axis has integer ticks
plt.title('Histogram of Betweenness Centrality - High Influence')
plt.show()
```

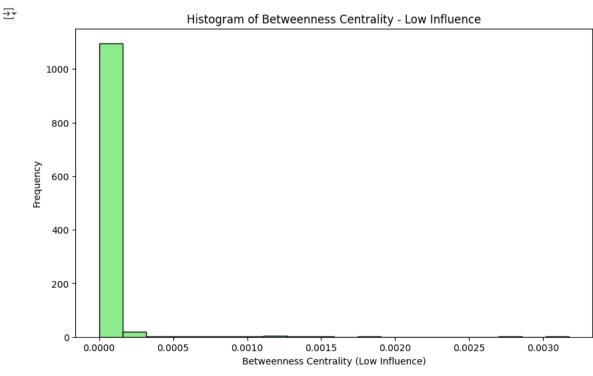


```
import random
import networkx as nx
import pandas as pd
import matplotlib.pyplot as plt
# Input and output file paths for high-influence replies
input\_file = '\underline{/content/drive/My~Drive/Colab}~Notebooks/cs131/replies\_nobots\_uniq\_highinfluence.NONOUSER.txt'
sampled_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_highinfluence.txt'
# Step 1: Create a random 1% sample of the adjacency list
sampling_rate = 0.01
with open(input_file, 'r') as infile, open(sampled_file, 'w') as outfile:
    for line in infile:
        if random.random() < sampling_rate: # Keep 1% of lines randomly</pre>
           outfile.write(line)
print(f"Random sample saved to: {sampled_file}")
# Step 2: Load the sampled adjacency list into a NetworkX graph
G_high = nx.read_edgelist(sampled_file, delimiter='\t', create_using=nx.Graph())
# Step 3: Calculate Betweenness Centrality
betweenness_centrality_high = nx.betweenness_centrality(G_high)
# Step 4: Save Betweenness Centrality to a file
betweenness_df_high = pd.DataFrame(list(betweenness_centrality_high.items()), columns=['Node', 'Betweenness Centrality'])
betweenness_df_high.to_csv('/content/drive/My_Drive/Colab_Notebooks/cs131/betweenness_centrality_sampled_high_replies.tsv', sep='\t', index=False)
plt.figure(figsize=(10, 6))
plt.hist(betweenness_centrality_high.values(), bins=20, color='skyblue', edgecolor='black')
plt.xlabel('Betweenness Centrality (High-Influence Replies - Sampled Data)')
plt.ylabel('Frequency')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True) # Ensure y-axis has integer ticks
plt.title('Histogram of Betweenness Centrality - High-Influence Replies (Sampled)')
plt.show()
```

Random sample saved to: /content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_highinfluence.txt



```
# Create a 1% Random Sample from the Large File
import random
# Input and output file paths
input_file = '/content/drive/My Drive/Colab Notebooks/cs131/lowinfl_AdjList.tsv'
output_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_lowinfl_AdjList.tsv'
# Define sampling rate (1%)
sampling_rate = 0.01
# Create a random sample
with open(input_file, 'r') as infile, open(output_file, 'w') as outfile:
    for line in infile:
       if random.random() < sampling_rate: # Keep 1% of lines randomly</pre>
           outfile.write(line)
print(f"Random sample saved to: {output_file}")
# Load the Sampled File into a NetworkX Graph
import networkx as nx
import pandas as pd
# Load the sampled adjacency list
sampled_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_lowinfl_AdjList.tsv'
G = nx.read_edgelist(sampled_file, delimiter='\t')
# Calculate betweenness centrality
centrality = nx.betweenness_centrality(G)
\# Save centrality to a file
centrality_df = pd.DataFrame(list(centrality.items()), columns=['Node', 'Betweenness Centrality'])
centrality_output = '/content/drive/My Drive/Colab Notebooks/cs131/betweenness_centrality_sampled_low.tsv'
centrality_df.to_csv(centrality_output, sep='\t', index=False)
print(f"Betweenness centrality calculated and saved to: {centrality_output}")
    Random sample saved to: /content/drive/My Drive/Colab Notebooks/cs131/sampled_lowinfl_AdjList.tsv
     Betweenness centrality calculated and saved to: /content/drive/My Drive/Colab Notebooks/cs131/betweenness_centrality_sampled_low.tsv
import matplotlib.pyplot as plt
# Plot histogram for betweenness centrality
plt.figure(figsize=(10, 6))
plt.hist(centrality.values(), bins=20, color='lightgreen', edgecolor='black')
plt.xlabel('Betweenness Centrality (Low Influence)')
plt.ylabel('Frequency')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True) # Ensure y-axis has integer ticks
plt.title('Histogram of Betweenness Centrality - Low Influence')
plt.show()
```



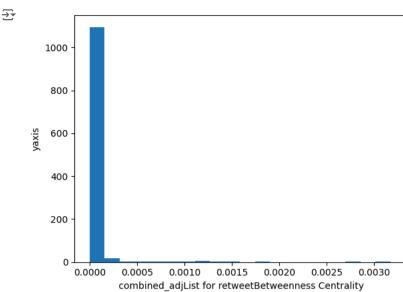
import random
import networkx as nx
import pandas as pd
import matplotlib.pyplot as plt

```
# Input and output file paths for low-influence replies
input\_file = \begin{tabular}{ll} input\_file = \begin{tabular}{ll} '\_content/drive/My & Drive/Colab \end{tabular} Notebooks/cs131/replies\_nobots\_uniq\_lowinfluence.NONOUSER.txt' \end{tabular}
sampled_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_lowinfluence.txt'
# Step 1: Create a random 1% sample of the adjacency list
sampling_rate = 0.01
with open(input_file, 'r') as infile, open(sampled_file, 'w') as outfile:
       if random.random() < sampling_rate: # Keep 1% of lines randomly</pre>
           outfile.write(line)
print(f"Random sample saved to: {sampled_file}")
\mbox{\tt\#} Step 2: Load the sampled adjacency list into a NetworkX graph
G_low = nx.read_edgelist(sampled_file, delimiter='\t', create_using=nx.Graph())
# Step 3: Calculate Betweenness Centrality
betweenness_centrality_low = nx.betweenness_centrality(G_low)
# Step 4: Save Betweenness Centrality to a file
betweenness_df_low = pd.DataFrame(list(betweenness_centrality_low.items()), columns=['Node', 'Betweenness Centrality'])
betweenness_df_low.to_csv('/content/drive/My Drive/Colab Notebooks/cs131/betweenness_centrality_sampled_low_replies.tsv', sep='\t', index=False)
# Step 5: Plot histogram for Betweenness Centrality
plt.figure(figsize=(10, 6))
plt.hist(betweenness_centrality_low.values(), bins=20, color='lightgreen', edgecolor='black')
plt.xlabel('Betweenness Centrality (Low-Influence Replies - Sampled Data)')
plt.ylabel('Frequency')
plt.title('Histogram of Betweenness Centrality - Low-Influence Replies (Sampled)')
```

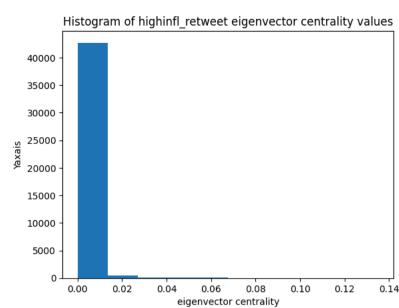
Random sample saved to: /content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_lowinfluence.txt

Histogram of Betweenness Centrality - Low-Influence Replies (Sampled) 120 100 80 60 40 20 0.0002 0.0003 0.0004 0.0005 0.0006 0.0000 0.0001 0.0007 0.0008 Betweenness Centrality (Low-Influence Replies - Sampled Data)

```
# Create a 1% Random Sample from the Large File
import random
# Input and output file paths
input_file = '/content/drive/My Drive/Colab Notebooks/cs131/combined_AdjList.tsv'
output_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_combined_AdjList.tsv'
# Define sampling rate (1%)
sampling_rate = 0.01
# Create a random sample
with open(input_file, 'r') as infile, open(output_file, 'w') as outfile:
    for line in infile:
       if random.random() < sampling_rate: # Keep 1% of lines randomly</pre>
           outfile.write(line)
print(f"Random sample saved to: {output_file}")
# Load the Sampled File into a NetworkX Graph
import networkx as nx
import pandas as pd
# Load the sampled adjacency list
sampled_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_combined_AdjList.tsv'
G = nx.read_edgelist(sampled_file, delimiter='\t')
# Calculate betweenness centrality
centrality = nx.betweenness_centrality(G)
# Save centrality to a file
centrality_df = pd.DataFrame(list(centrality.items()), columns=['Node', 'Betweenness Centrality'])
centrality_output = '/content/drive/My Drive/Colab Notebooks/cs131/betweenness_centrality_sampled_combined.tsv'
centrality_df.to_csv(centrality_output, sep='\t', index=False)
print(f"Betweenness centrality calculated and saved to: {centrality_output}")
Random sample saved to: /content/drive/My Drive/Colab Notebooks/cs131/sampled_combined_AdjList.tsv
     Betweenness centrality calculated and saved to: /content/drive/My Drive/Colab Notebooks/cs131/betweenness_centrality_sampled_combined.tsv
#plot on histogram
plt.hist(centrality.values(),bins=20)
plt.xlabel(' combined_adjList for retweetBetweenness Centrality')
plt.ylabel('yaxis')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True)
plt.show()
```



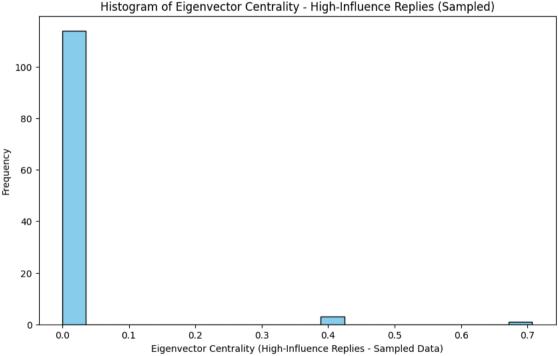
```
Eigenvector centrality
#Load the adjcency list from a tsv file
file_path = '/content/drive/My Drive/Colab Notebooks/cs131/highinfl_AdjList.tsv'
\#calculate the betweenness centrality of eACH NODE
\verb|eigenvector_centrality=nx.eigenvector_centrality(G,max\_iter=1000)|\\
#find the max node with eigenvector centrality
max_node=max(eigenvector_centrality,key=eigenvector_centrality.get)
print('Node',max_node,'has the maximum eigenvector centrality of',eigenvector_centrality[max_node])
Node 723757332 has the maximum eigenvector centrality of 0.13528186100663186
#print the eigenvector centrality values
for node,ec in eigenvector_centrality.items():
    print(f"{node}:{ec}")
    Streaming output truncated to the last 5000 lines.
     1111094288467800064:9.593449465975177e-08
     1151822814846029824:9.593449465975177e-08
     1194244593170231296:9.593449465975177e-08
     1213953152:9.593449465975177e-08
     1307690532215435264:9.593449465975177e-08
     1330349107:9.593449465975177e-08
     1359952496140156933:9.593449465975177e-08
     1364874243557752833:9.593449465975177e-08
     1387674053389873152:9.593449465975177e-08
     1425101591313530886:9.593449465975177e-08
     1425943814137651212:9.593449465975177e-08
     1440635012:9.593449465975177e-08
     1504202114129530881:9.593449465975177e-08
     1512644840131026949:9.593449465975177e-08
     1525234429:9.593449465975177e-08
     166883389:9.593449465975177e-08
     17092592:9.593449465975177e-08
     19534496:9.593449465975177e-08
     2316064569:9.593449465975177e-08
     23294237:9.593449465975177e-08
     2445637219:9.593449465975177e-08
     263327246:9.593449465975177e-08
     2795748238:9.593449465975177e-08
     291521804:9.593449465975177e-08
     302491448:9.593449465975177e-08
     3060891761:9.593449465975177e-08
     3128782139:9.593449465975177e-08
     31503048:9.593449465975177e-08
     33482561:9.593449465975177e-08
     454696257:9.593449465975177e-08
     4788937961:9.593449465975177e-08
     48575074:9.593449465975177e-08
     485860087:9.593449465975177e-08
     833170111:9.593449465975177e-08
     90996954:9.593449465975177e-08
     975558929584279552:9.593449465975177e-08
     984989302550552576:9.593449465975177e-08
     111400999:1.3380893514116763e-05
     1121789470171258880:1.3380893514116763e-05
     1274803192203579392:1.3380893514116763e-05
     1296035989:1.3380893514116763e-05
     1319523522:1.3380893514116763e-05
     1326272512808857641:1.3380893514116763e-05
     1383377382824837130:1.3380893514116763e-05
     1403537423905169412:1.3380893514116763e-05
     1403713091972571136:1.3380893514116763e-05
     1447742440291504128:1.3380893514116763e-05
     1457894861311549444:1.3380893514116763e-05
     14730894:1.3380893514116763e-05
     177564016:1.3380893514116763e-05
     2301990517:1.3380893514116763e-05
     242694418:1.3380893514116763e-05
     2908170952:1.3380893514116763e-05
     394147536:1.3380893514116763e-05
     466864852:1.3380893514116763e-05
     4765364386:1.3380893514116763e-05
     4780832983:1.3380893514116763e-05
#plt a histogram of the data
plt.hist(eigenvector_centrality.values(), bins=10)
#Add labels and a title to the plot
plt.xlabel('eigenvector centrality')
plt.ylabel('Yaxais')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True)
plt.title('Histogram of highinfl_retweet eigenvector centrality values')
#show the plot
plt.show()
```



₹

```
import random
import networkx as nx
import pandas as pd
import matplotlib.pyplot as plt
# Input and output file paths for high-influence replies
input_file = '/content/drive/My Drive/Colab Notebooks/cs131/replies_nobots_uniq_highinfluence.NONOUSER.txt'
sampled_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_highinfluence.txt'
# Step 1: Create a random 1% sample of the adjacency list
sampling_rate = 0.01
with open(input_file, 'r') as infile, open(sampled_file, 'w') as outfile:
    for line in infile:
       if random.random() < sampling_rate: # Keep 1% of lines randomly</pre>
            outfile.write(line)
print(f"Random sample saved to: {sampled_file}")
# Step 2: Load the sampled adjacency list into a NetworkX graph
G_high = nx.read_edgelist(sampled_file, delimiter='\t', create_using=nx.Graph())
# Step 3: Calculate Eigenvector Centrality
eigenvector_centrality_high = nx.eigenvector_centrality(G_high, max_iter=1000)
# Step 4: Save Eigenvector Centrality to a file
eigenvector\_df\_high = pd.DataFrame(list(eigenvector\_centrality\_high.items()), \ columns = ['Node', 'Eigenvector Centrality'])
eigenvector_df_high.to_csv('/content/drive/My Drive/Colab Notebooks/cs131/eigenvector_centrality_sampled_high_replies.tsv', sep='\t', index=False)
# Step 5: Plot histogram for Eigenvector Centrality
plt.figure(figsize=(10, 6))
plt.hist(eigenvector_centrality_high.values(), bins=20, color='skyblue', edgecolor='black')
plt.xlabel('Eigenvector Centrality (High-Influence Replies - Sampled Data)')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True) # Ensure y-axis has integer ticks
plt.title('Histogram of Eigenvector Centrality - High-Influence Replies (Sampled)')
plt.show()
```

Random sample saved to: /content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_highinfluence.txt



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

file_path = '/content/drive/My Drive/Colab Notebooks/cs131/lowinfl_AdjList.tsv'

# Load the adjacency list into a NetworkX graph
G = nx.read_edgelist(file_path, delimiter='\t')

#calculate the betweenness centrality of eACH NODE
eig_cen=nx.eigenvector_centrality(G,max_iter=1000)

#find the max node with eigenvector centrality
max_node=max(eig_cen,key=eig_cen.get)

print('Node',max_node,'has the maximum eigenvector centrality of',eig_cen[max_node])
```

Node 2189523500 has the maximum eigenvector centrality of 0.47240487766026906

```
#print the eigenvector centrality values
for node,ec in eig_cen.items():
    print(f"{node}:{ec}")
```

```
Streaming output truncated to the last 5000 lines.

121594232:4.739629457431875e-07

1216813913150500866:4.739629457431875e-07

1221016504067592193:4.739629457431875e-07

1221377785:4.739629457431875e-07

1228274850822840320:4.739629457431875e-07

1231878704743223296:4.739629457431875e-07
```

1232653578055147522:4.739629457431875e-07
1235955986810232833:4.739629457431875e-07
1241760253:4.739629457431875e-07
1242142822532292608:4.739629457431875e-07
1250047514021171201:4.739629457431875e-07

1251761794974015491:4.739629457431875e-07 125362283:4.739629457431875e-07 1260946135797190656:4.739629457431875e-07 1280540497:4.560952171757735e-06

1280540497:4.560952171757735e-06 1287118441007259649:4.739629457431875e-07 128968687:4.739629457431875e-07

129963753:4.739629457431875e-07 1304589818:4.739629457431875e-07 130555328:4.739629457431875e-07 130640704:4.739629457431875e-07

1308253814:4.739629457431875e-07 1315972154517794822:4.739629457431875e-07 1316398228569546755:4.739629457431875e-07 1323634389050339328:4.739629457431875e-07

1324698582495203330:4.739629457431875e-07 1325265709:4.739629457431875e-07 1326873186596777985:4.739629457431875e-07 1328697528825618432:4.739629457431875e-07

1328699022:4.739629457431875e-07 1328788482353934340:4.739629457431875e-07 1334814328084688896:4.739629457431875e-07 1344651471858630656:4.739629457431875e-07

1344651471858630656:4.739629457431875e-07
1345677728138334208:4.739629457431875e-07
1346268799:4.739629457431875e-07
134793154:4.739629457431875e-07
1355553109959962628:4.739629457431875e-07

1355828513132187649:4.739629457431875e-07 1360292790:4.739629457431875e-07 1363174494299430914:4.739629457431875e-07 1367853648:4.739629457431875e-07

1377269138:4.739629457431875e-07 1378947769184976896:4.739629457431875e-07 1379292876:4.739629457431875e-07 1379638549:4.739629457431875e-07 1381715133706162176:4.739629457431875e-07

1381715133706162176:4.739629457431875e-07
138363206:4.739629457431875e-07
139230276:4.739629457431875e-07
1397240360338956292:4.739629457431875e-07
1398234331135500292:4.739629457431875e-07

1400580861150613506:4.739629457431875e-07 1400783012:4.739629457431875e-07 14048767:4.739629457431875e-07 14275715:4.739629457431875e-07

1430446644571607045:4.739629457431875e-07 1433791346:4.739629457431875e-07 1439338194:4.739629457431875e-07

Input and output file paths for low-influence replies

#plt a histogram of the data
plt.hist(eig_cen.values(), bins=10)
#Add labels and a title to the plot
plt.xlabel('eigenvector centrality')
plt.ylabel('Frequency')

plt.ylabel('Frequency')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True)
plt.title('Histogram of Low eigenvector centrality values for retweet')
#show the plot

plt.show()

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Histogram of Low eigenvector centrality values for retweet 40000 35000 30000 25000 20000 15000 10000 5000 0 0.1 0.0 0.2 0.3 0.4 eigenvector centrality

```
input\_file = '\underline{/content/drive/My\ Drive/Colab}\ Notebooks/cs131/replies\_nobots\_uniq\_lowinfluence.NONOUSER.txt'
sampled_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_lowinfluence.txt'
# Step 1: Create a random 1% sample of the adjacency list
sampling_rate = 0.01
with open(input_file, 'r') as infile, open(sampled_file, 'w') as outfile:
    for line in infile:
       if random.random() < sampling_rate: # Keep 1% of lines randomly</pre>
            outfile.write(line)
print(f"Random sample saved to: {sampled_file}")
\# Step 2: Load the sampled adjacency list into a NetworkX graph
G_low = nx.read_edgelist(sampled_file, delimiter='\t', create_using=nx.Graph())
# Step 3: Calculate Eigenvector Centrality
eigenvector_centrality_low = nx.eigenvector_centrality(G_low, max_iter=1000)
# Step 4: Save Eigenvector Centrality to a file
eigenvector_df_low = pd.DataFrame(list(eigenvector_centrality_low.items()), columns=['Node', 'Eigenvector Centrality'])
eigenvector_df_low.to_csv('/content/drive/My Drive/Colab Notebooks/cs131/eigenvector_centrality_sampled_low_replies.tsv', sep='\t', index=False)
# Step 5: Plot histogram for Eigenvector Centrality
plt.figure(figsize=(10, 6))
```

thality law values() hins-20 colon-'lightgreen' edgecolon-'hlack')

```
plt.xlabel('Eigenvector Centrality (Low-Influence Replies - Sampled Data)')
plt.ylabel('Frequency')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True) # Ensure y-axis has integer ticks
plt.title('Histogram of Eigenvector Centrality - Low-Influence Replies (Sampled)')
plt.show()
```

 $\begin{tabular}{ll} \hline \tt 3 \\ \hline \tt 3 \\ \hline \tt 4 \\ \hline \tt 5 \\ \hline \tt 6 \\ \hline \tt 7 \\$

```
Histogram of Eigenvector Centrality - Low-Influence Replies (Sampled)
  175
  150
   125
Frequency 100
    75
    50
    25
     0
           0.0
                        0.1
                                      0.2
                                                    0.3
                                                                 0.4
                                                                               0.5
                                                                                             0.6
                                                                                                          0.7
                               Eigenvector Centrality (Low-Influence Replies - Sampled Data)
```

Save combined_data as combined_AdjList.tsv combined_data.to_csv('/content/drive/My Drive/Colab Notebooks/cs131/combined_AdjList.tsv', sep='\t', index=False, header=False)

#print("File combined_AdjList.tsv has been created successfully.")

```
file_path = '/content/drive/My Drive/Colab Notebooks/cs131/combined_AdjList.tsv'
```

G = nx.read_edgelist(file_path, delimiter='\t')

#calculate the betweenness centrality of eACH NODE
eig_cen=nx.eigenvector_centrality(G,max_iter=1000)

#find the max node with eigenvector centrality
max_node=max(eig_cen,key=eig_cen.get)

print('Node',max_node,'has the maximum eigenvector centrality of',eig_cen[max_node])

 \rightarrow Node 723757332 has the maximum eigenvector centrality of 0.1352818610066319

#print the eigenvector centrality values
for node,ec in eig_cen.items():
 print(f"{node}:{ec}")

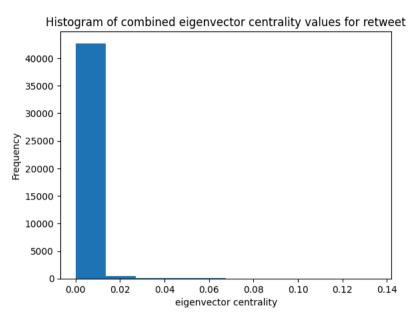
Streaming output truncated to the last 5000 lines. 1111094288467800064:9.593449465975177e-08

1151822814846029824:9.593449465975177e-08 1194244593170231296:9.593449465975177e-08 1213953152:9.593449465975177e-08 1307690532215435264:9.593449465975177e-08 1330349107:9.593449465975177e-08 1359952496140156933:9.593449465975177e-08 1364874243557752833:9.593449465975177e-08 1387674053389873152:9.593449465975177e-08 1425101591313530886:9.593449465975177e-08 1425943814137651212:9.593449465975177e-08 1440635012:9.593449465975177e-08 1504202114129530881:9.593449465975177e-08 1512644840131026949:9.593449465975177e-08 1525234429:9.593449465975177e-08 166883389:9.593449465975177e-08 17092592:9.593449465975177e-08 19534496:9.593449465975177e-08 2316064569:9.593449465975177e-08 23294237:9.593449465975177e-08 2445637219:9.593449465975177e-08 263327246:9.593449465975177e-08 2795748238:9.593449465975177e-08 291521804:9.593449465975177e-08 302491448:9.593449465975177e-08 3060891761:9.593449465975177e-08 3128782139:9.593449465975177e-08 31503048 • 9 . 593449465975177e - 08 33482561:9.593449465975177e-08 454696257:9.593449465975177e-08 4788937961:9.593449465975177e-08 48575074:9.593449465975177e-08 485860087:9.593449465975177e-08 833170111:9.593449465975177e-08 90996954:9.593449465975177e-08 975558929584279552:9.593449465975177e-08 984989302550552576:9.593449465975177e-08 111400999:1.3380893514116764e-05 1121789470171258880:1.3380893514116764e-05 1274803192203579392:1.3380893514116764e-05 1296035989:1.3380893514116764e-05 1319523522:1.3380893514116764e-05 1326272512808857641:1.3380893514116764e-05 1383377382824837130:1.3380893514116764e-05 1403537423905169412:1.3380893514116764e-05 1403713091972571136:1.3380893514116764e-05 1447742440291504128:1.3380893514116764e-05 1457894861311549444:1.3380893514116764e-05 14730894:1.3380893514116764e-05 177564016:1.3380893514116764e-05 2301990517:1.3380893514116764e-05

242694418:1.3380893514116764e-05 2908170952:1.3380893514116764e-05 12/4/24, 10:20 PM A6.ipynb - Colab

```
394147536:1.3380893514116764e-05
466864852:1.3380893514116764e-05
4765364386:1.3380893514116764e-05
4780832983:1.3380893514116764e-05

#plt a histogram of the data
plt.hist(eig_cen.values(), bins=10)
#Add labels and a title to the plot
plt.xlabel('eigenvector centrality')
plt.ylabel('Frequency')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True)
plt.title('Histogram of combined eigenvector centrality values for retweet')
#show the plot
plt.show()
```



K-core centrality

₹

```
import pandas as pd
import networkx as nx
{\tt import\ matplotlib.pyplot\ as\ plt}
import networkx as nx
file\_path = '/content/drive/My \ Drive/Colab \ Notebooks/cs131/retweets\_nobots\_uniq\_highinfluence.NONOUSER.txt' \ Notebooks/cs131/retweets\_nobots\_nobots\_uniq\_highinfluence.NONOUSER.txt' \ Notebooks/cs131/retweets\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_nobots\_
# Load the adjacency list
G = nx.read_edgelist(file_path, delimiter='\t')
#calculate K-core decomposition
k_core_centralities=nx.core_number(G)
#find the max node for k-core centralities for high
\verb|max_k_core_centralities=[node for node,k_core_centrality in k_core_centralities.items() if k_core_centrality==max(k_core_centralities.values())]|
\hbox{\it\#print the nodes with maximum $k\_$ core centrality for high}
print("The nodes with the maximum k_core centrality value are")
for node in \max_k_core_centralities:
          print(node)
          The nodes with the maximum k_core centrality value are
 \overline{\mathbf{T}}
             105327432
             1205226529455632385
             163018653
             16563015
             1891490382
             299273962
             30844417
             3129968261
             380648579
             586291040
             67934675
             720139699
             879147821915615233
             985749294
            1010308883896774656
            1120633726478823425
             1168793622248067072
             118459189
             1219232377605644289
             1238583088998830081
            1296279134079823872
             1314241954058833926
             14106476
             143427448
             18831926
            2260170266
             2420267570
            2561718665
             2573480784
             2749315621
             27493883
             2758100418
             27831488
             279390084
             3003886063
             304679484
            33727663
             3972812140
             469509327
             832524310199824384
             873135988440223745
             87358629
             939486738543796224
            1252988129708929024
            15480566
            953924228306305024
            1495480590572961792
            1640929196
```

```
1028022611324747776
1003107003693137921
1005846500583321601
1045110787
1243560408025198593

#plot histogram of k-Core centrality
#plt a histogram of the data
plt.hist(list(k_core_centralities.values()))
```

```
#show the plot plt.show()

Histogram of high k_corecentrality values for retweet

3500

3000

2500

1500

1500

500
```

10

15

plt.gca().get_yaxis().get_major_locator().set_params(integer=True)
plt.title('Histogram of high k_corecentrality values for retweet')

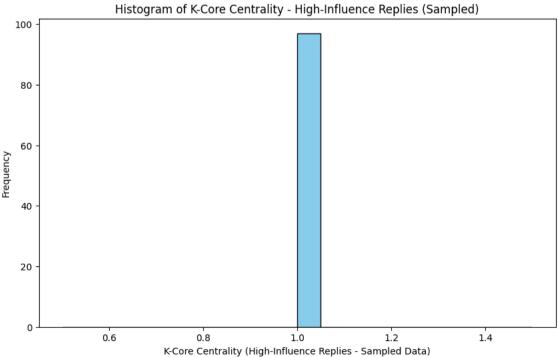
#Add labels and a title to the plot
plt.xlabel('k_core_centrality for highinfl')

plt.ylabel('Yaxais')

0 7

```
k_core_centrality for highinfl
import random
import networkx as nx
import pandas as pd
import matplotlib.pyplot as plt
# Input and output file paths for high-influence replies
input_file = '/content/drive/My Drive/Colab Notebooks/cs131/replies_nobots_uniq_highinfluence.NONOUSER.txt'
sampled_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_highinfluence.txt'
# Step 1: Create a random 1% sample of the adjacency list
sampling_rate = 0.01
with open(input_file, 'r') as infile, open(sampled_file, 'w') as outfile:
    for line in infile:
       if random.random() < sampling_rate: # Keep 1% of lines randomly</pre>
            outfile.write(line)
print(f"Random sample saved to: {sampled_file}")
# Step 2: Load the sampled adjacency list into a NetworkX graph
G_high = nx.read_edgelist(sampled_file, delimiter='\t', create_using=nx.Graph())
# Step 3: Calculate K-Core Centrality (coreness)
k_core_high = nx.core_number(G_high)
# Step 4: Save K-Core Centrality to a file
k_core_df_high = pd.DataFrame(list(k_core_high.items()), columns=['Node', 'K-Core'])
k_core_df_high.to_csv('<u>/content/drive/My Drive/Colab</u> Notebooks/cs131/k_core_centrality_sampled_high_replies.tsv', sep='\t', index=False)
# Step 5: Plot histogram for K-Core Centrality
plt.figure(figsize=(10, 6))
plt.hist(k_core_high.values(), bins=20, color='skyblue', edgecolor='black')
plt.xlabel('K-Core Centrality (High-Influence Replies - Sampled Data)')
plt.ylabel('Frequency')
plt.title('Histogram of K-Core Centrality - High-Influence Replies (Sampled)')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True) # Ensure y-axis has integer ticks
plt.show()
```





import networkx as nx

file_path = '/content/drive/My Drive/Colab Notebooks/cs131/retweets_nobots_uniq_lowinfluence.NONOUSER.txt'

```
# Load the adjacency list
G = nx.read_edgelist(file_path, delimiter='\t')
```

```
#calculate K-core decomposition
k_core_centralities=nx.core_number(G)
\hbox{\it \#find the max node for $k$-core centralities for high}\\
max\_k\_core\_centralities=[node\ for\ node,k\_core\_centrality=max(k\_core\_centralities.values())]
\hbox{\it\#print the nodes with maximum $k\_$ core centrality for high}
\label{lem:print} \mbox{print("The nodes with the maximum $k$\_core centrality value are")}
for node in {\tt max\_k\_core\_centralities}\colon
    print(node)
\rightarrow The nodes with the maximum k_core centrality value are
     2189523500
     1016943828052336640
     1238370241169616897
     132731802
     1382912376597479427
     1573800344
     173672963
     18965916
     198296897
     209535365
     2479226604
     258124400
     29420301
352754946
     48624704
     588732151
     58974496
     66917778
     711750460932141056
     764657028
     766136186268160000
     79402753
870629200348274688
     926019424154349568
     2574271742
     559681926
     629280862
     551483643
#print the eigenvector centrality values
for node in k_core_centralities:
    print(node)
    Streaming output truncated to the last 5000 lines.
     121594232
     1216813913150500866
     1221016504067592193
     1221377785
     1228274850822840320
     1231878704743223296
     1232653578055147522
     1235955986810232833
     1241760253
     1242142822532292608
     1250047514021171201
     1251761794974015491
     125362283
     1260946135797190656
     1280540497
     1287118441007259649
     128968687
     129963753
     1304589818
     130555328
     130640704
     1308253814
     1315972154517794822
     1316398228569546755
     1323634389050339328
     1324698582495203330
     1325265709
     1326873186596777985
     1328697528825618432
     1328699022
     1328788482353934340
     1334814328084688896
     1344651471858630656
     1345677728138334208
     1346268799
     134793154
     1355553109959962628
     1355828513132187649
     1360292790
1363174494299430914
     1367853648
     1377269138
     1378947769184976896
     1379292876
     1379638549
     1381715133706162176
     138363206
     139230276
     1397240360338956292
     13982343311355
     1400580861150613506
     1400783012
     14048767
     14275715
     1430446644571607045
     1433791346
     1439338194
\#plot histogram of k-Core centrality
#plt a histogram of the data
plt.hist(list(k core centralities.values()))
#Add labels and a title to the plot
plt.xlabel('k_core_centrality for lowinfl')
plt.ylabel('Yaxais')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True)
```

plt.title('Histogram of low k_corecentrality values for retweet')

#show the plot
plt.show()

12/4/24, 10:20 PM A6.ipynb - Colab

```
\overline{\mathbf{T}}
                     Histogram of low k_corecentrality values for retweet
         35000
         30000
         25000
        20000
         15000
         10000
          5000
                                      k_core_centrality for lowinfl
```

import networkx as nx

```
file_path = '/content/drive/My Drive/Colab Notebooks/cs131/retweets_nobots_uniq_lowinfluence.NONOUSER.txt'
```

```
# Load the adjacency list
G = nx.read_edgelist(file_path, delimiter='\t')
```

#calculate K-core decomposition k_core_centralities=nx.core_number(G)

#find the max node for k-core centralities for high $\label{lem:max_k_core_centralities} \\ \texttt{max_k_core_centralities.items()} \\ \texttt{in k_core_centralities.items()} \\ \texttt{if k_core_centrality==max(k_core_centralities.values())} \\ \\ \texttt{max_k_core_centralities=[node for node,k_core_centrality in k_core_centralities.items())} \\ \texttt{max_k_k_core_centralities=[node for node,k_core_centralities.items())} \\ \texttt{max_k_k_core_centralities=[node for node,k_core_centralities.items())} \\ \texttt{max_k_k_core_centralities=[node for node,k_core_centralities.items())} \\ \texttt{max_k_k_core_centralities=[node for node,k_core_centralities.items())} \\ \texttt{max_k_k_core_centralities=[node for node,k_core_centralities=[node for node,k_core_$

#print the nodes with maximum k_core centrality for high print("The nodes with the maximum k_core centrality value are") for node in $\max_k_core_centralities$: print(node)

The nodes with the maximum k_core centrality value are

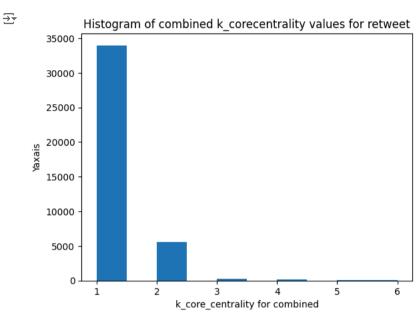
#print the eigenvector centrality values for node in $k_core_centralities$: print(node)

\Rightarrow Streaming output truncated to the last 5000 lines. 121594232

```
1379292876
1379638549
1381715133706162176
138363206
139230276
1397240360338956292
1398234331135500292
1400580861150613506
1400783012
14048767
14275715
1430446644571607045
1433791346
1439338194

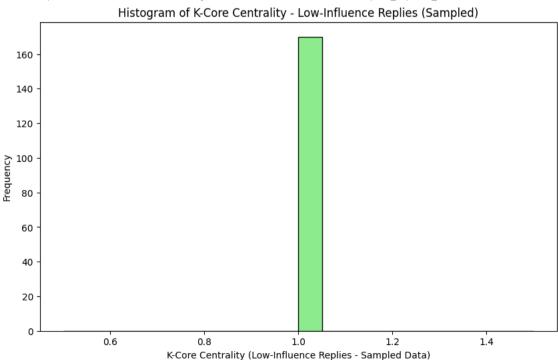
Solot histogram of k-Core centrallation in the data
```

#plot histogram of k-Core centrality
#plt a histogram of the data
plt.hist(list(k_core_centralities.values()))
#Add labels and a title to the plot
plt.xlabel('k_core_centrality for combined')
plt.ylabel('Yaxais')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True)
plt.title('Histogram of combined k_corecentrality values for retweet')
#show the plot
plt.show()



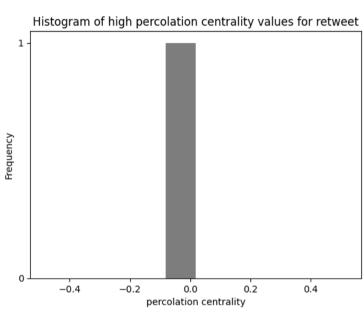
```
# Input and output file paths for low-influence replies
input_file = '/content/drive/My Drive/Colab Notebooks/cs131/replies_nobots_uniq_lowinfluence.NONOUSER.txt'
sampled_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_lowinfluence.txt'
# Step 1: Create a random 1% sample of the adjacency list
sampling_rate = 0.01
with open(input_file, 'r') as infile, open(sampled_file, 'w') as outfile:
    for line in infile:
       if random.random() < sampling_rate: # Keep 1% of lines randomly</pre>
            outfile.write(line)
print(f"Random sample saved to: {sampled_file}")
# Step 2: Load the sampled adjacency list into a NetworkX graph
G_low = nx.read_edgelist(sampled_file, delimiter='\t', create_using=nx.Graph())
# Step 3: Calculate K-Core Centrality (coreness)
k_core_low = nx.core_number(G_low)
# Step 4: Save K-Core Centrality to a file
k_core_df_low = pd.DataFrame(list(k_core_low.items()), columns=['Node', 'K-Core'])
\label{low.to_csv('/content/drive/My Drive/Colab Notebooks/cs131/k_core_centrality_sampled_low_replies.tsv', sep='\t', index=False)} \\
# Step 5: Plot histogram for K-Core Centrality
plt.figure(figsize=(10, 6))
\verb|plt.hist(k_core_low.values(), bins=20, color='lightgreen', edgecolor='black')| \\
plt.xlabel('K-Core Centrality (Low-Influence Replies - Sampled Data)')
plt.ylabel('Frequency')
plt.title('Histogram of K-Core Centrality - Low-Influence Replies (Sampled)')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True) # Ensure y-axis has integer ticks
plt.show()
```

Random sample saved to: /content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_lowinfluence.txt



Percolation centrality

```
import networkx as nx
file_path = '/content/drive/My Drive/Colab Notebooks/cs131/retweets_nobots_uniq_highinfluence.NONOUSER.txt'
# Load the adjacency list
G = nx.read_edgelist(file_path, delimiter='\t')
#calculate the optimal percolation centralities
percolation_centralities={}
for node in G.nodes():
    \#calculate the reduced degree centrality of all nodes at a distance of 1 from the node
    reduced\_degree\_centrality = nx.degree\_centrality(G)[node]/max(nx.degree\_centrality(G).values())
#calculate the total reduced degree centrality of all nodees at a distance of 1 from the node
total_reduced_degree_centrality=1
for neighbor in G.neighbors(node):
    total_reduced_degree_centrality*=(1-nx.degree_centrality(G)[neighbor]/max(nx.degree_centrality(G).values()))
#calculate the percolation centralities
\verb|percolation_centrality=reduced_degree_centrality*total_reduced_degree_centrality| \\
#Add the percolation centrality
\verb"percolation_centralities[node]="percolation_centrality"
print(percolation_centralities[node])
→ 0.01872640328844575
#plt a histogram of the data
plt.hist(percolation_centralities.values(), bins=10,color='grey')
#Add labels and a title to the plot
plt.xlabel('percolation centrality')
plt.ylabel('Frequency')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True)
plt.title('Histogram of high percolation centrality values for retweet')
#show the plot
plt.show()
₹
            Histogram of high percolation centrality values for retweet
         1
```

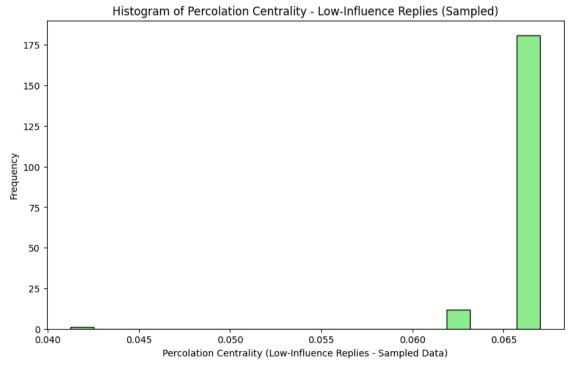


```
import random
import networkx as nx
import pandas as pd
{\tt import\ matplotlib.pyplot\ as\ plt}
# Input and output file paths for high-influence replies
input_file = '/content/drive/My Drive/Colab Notebooks/cs131/replies_nobots_uniq_highinfluence.NONOUSER.txt'
sampled_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_highinfluence.txt'
# Step 1: Create a random 1% sample of the adjacency list
sampling_rate = 0.01
with open(input_file, 'r') as infile, open(sampled_file, 'w') as outfile:
    for line in infile:
        if random.random() < sampling_rate: # Keep 1% of lines randomly</pre>
           outfile.write(line)
print(f"Random sample saved to: {sampled_file}")
# Step 2: Load the sampled adjacency list into a NetworkX graph
G_high = nx.read_edgelist(sampled_file, delimiter='\t', create_using=nx.Graph())
# Step 3: Calculate Percolation Centrality (approximated as node connectivity impact)
percolation_centrality_high = {}
for node in G_high:
    G_copy = G_high.copy()
    G_copy.remove_node(node)
    largest_component = max(nx.connected_components(G_copy), key=len, default=[])
    percolation_centrality_high[node] = len(largest_component) / len(G_high)
# Step 4: Save Percolation Centrality to a file
percolation_df_high = pd.DataFrame(list(percolation_centrality_high.items()), columns=['Node', 'Percolation Centrality'])
percolation_df_high.to_csv('/content/drive/My Drive/Colab Notebooks/cs131/percolation_centrality_sampled_high_replies.tsv', sep='\t', index=False)
# Step 5: Plot histogram for Percolation Centrality
plt.figure(figsize=(10, 6))
plt.hist(percolation_centrality_high.values(), bins=20, color='skyblue', edgecolor='black')
plt.xlabel('Percolation Centrality (High-Influence Replies - Sampled Data)')
plt.ylabel('Frequency')
plt.title('Histogram of Percolation Centrality - High-Influence Replies (Sampled)')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True) # Ensure y-axis has integer ticks
```

Random sample saved to: /content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_highinfluence.txt

```
# Input and output file paths for low-influence replies
input_file = '/content/drive/My Drive/Colab Notebooks/cs131/replies_nobots_uniq_lowinfluence.NONOUSER.txt'
sampled_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_lowinfluence.txt'
# Step 1: Create a random 1% sample of the adjacency list
sampling_rate = 0.01
with open(input_file, 'r') as infile, open(sampled_file, 'w') as outfile:
    for line in infile:
       if random.random() < sampling_rate: # Keep 1% of lines randomly</pre>
           outfile.write(line)
print(f"Random sample saved to: {sampled_file}")
# Step 2: Load the sampled adjacency list into a NetworkX graph
G_low = nx.read_edgelist(sampled_file, delimiter='\t', create_using=nx.Graph())
# Step 3: Calculate Percolation Centrality (approximated as node connectivity impact)
percolation centrality low = {}
for node in G_low:
   G_copy = G_low.copy()
   G_copy.remove_node(node)
   largest_component = max(nx.connected_components(G_copy), key=len, default=[])
   percolation_centrality_low[node] = len(largest_component) / len(G_low)
# Step 4: Save Percolation Centrality to a file
percolation\_df\_low = pd.DataFrame(list(percolation\_centrality\_low.items()), columns=['Node', 'Percolation Centrality'])
percolation_df_low.to_csv('/content/drive/My Drive/Colab Notebooks/cs131/percolation_centrality_sampled_low_replies.tsv', sep='\t', index=False)
# Step 5: Plot histogram for Percolation Centrality
plt.figure(figsize=(10, 6))
plt.hist(percolation_centrality_low.values(), bins=20, color='lightgreen', edgecolor='black')
plt.xlabel('Percolation Centrality (Low-Influence Replies - Sampled Data)')
plt.ylabel('Frequency')
plt.title('Histogram of Percolation Centrality - Low-Influence Replies (Sampled)')
plt.show()
```

Random sample saved to: /content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_lowinfluence.txt



```
import networkx as nx

file_path = '/content/drive/My Drive/Colab Notebooks/cs131/retweets_nobots_uniq_lowinfluence.NONOUSER.txt'

# Load the adjacency list
G = nx.read_edgelist(file_path, delimiter='\t')

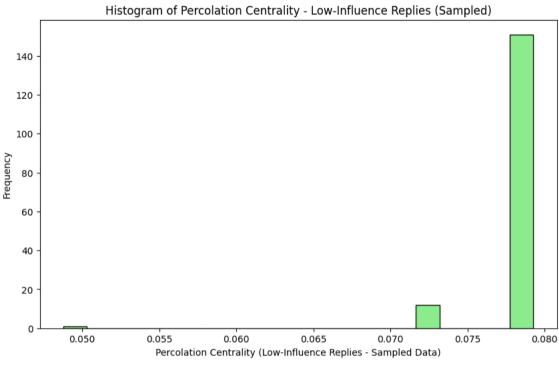
# Input and output file paths for low-influence replies
input_file = '/content/drive/My Drive/Colab Notebooks/cs131/replies_nobots_uniq_lowinfluence.NONOUSER.txt'
sampled_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_lowinfluence.txt'

# Step 1: Create a random 1% sample of the adjacency list
sampling_rate = 0.01
with open(input_file, 'r') as infile, open(sampled_file, 'w') as outfile:
    for line in infile:
        if random.random() < sampling_rate: # Keep 1% of lines randomly</pre>
```

outfile.write(line)

```
print(f"Random sample saved to: {sampled_file}")
\mbox{\#} Step 2: Load the sampled adjacency list into a NetworkX graph
G_low = nx.read_edgelist(sampled_file, delimiter='\t', create_using=nx.Graph())
# Step 3: Calculate Percolation Centrality (approximated as node connectivity impact)
percolation_centrality_low = {}
for node in G low:
    G_{copy} = G_{low.copy}()
    {\tt G\_copy.remove\_node(node)}
    largest_component = max(nx.connected_components(G_copy), key=len, default=[])
    percolation_centrality_low[node] = len(largest_component) / len(G_low)
# Step 4: Save Percolation Centrality to a file
percolation\_df\_low = pd.DataFrame(list(percolation\_centrality\_low.items()), \ columns=['Node', 'Percolation Centrality'])
percolation_df_low.to_csv('<u>/content/drive/My_Drive/Colab</u>_Notebooks/cs131/percolation_centrality_sampled_low_replies.tsv', sep='\t', index=False)
# Step 5: Plot histogram for Percolation Centrality
plt.figure(figsize=(10, 6))
\verb|plt.hist(percolation_centrality_low.values(), bins=20, color='lightgreen', edgecolor='black')| \\
plt.xlabel('Percolation Centrality (Low-Influence Replies - Sampled Data)')
plt.ylabel('Frequency')
plt.title('Histogram of Percolation Centrality - Low-Influence Replies (Sampled)')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True) # Ensure y-axis has integer ticks
plt.show()
```

Random sample saved to: /content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_lowinfluence.txt



#calculate the total reduced degree centrality of all nodees at a distance of 1 from the node
total_reduced_degree_centrality=1
for neighbor in G.neighbors(node):

total_reduced_degree_centrality*=(1-nx.degree_centrality(G)[neighbor]/max(nx.degree_centrality(G).values()))

#calculate the percolation centralities
percolation_centrality=reduced_degree_centrality*total_reduced_degree_centrality

print(percolation_centralities[node])

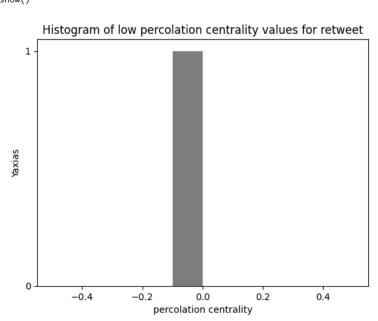
 $\verb"percolation_centralities[node]="percolation_centrality" \\$

→ 0.001019608657074216

₹

#Add the percolation centrality

#plt a histogram of the data
plt.hist(percolation_centralities.values(), bins=10,color='grey')
#Add labels and a title to the plot
plt.xlabel('percolation centrality')
plt.ylabel('Yaxias')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True)
plt.title('Histogram of low percolation centrality values for retweet')
#show the plot
plt.show()



file_path = '/content/drive/My Drive/Colab Notebooks/cs131/combined_AdjList.tsv'

G = nx.read_edgelist(file_path, delimiter='\t')

#calculate the optimal percolation centralities
percolation centralities={}

percolation_centralities={}

```
# for node in G.nodes():
     #calculate the reduced degree centrality of all nodes at a distance of 1 from the node
     reduced\_degree\_centrality = (G)[node]/max(nx.degree\_centrality(G).values())
\# calculate the total reduced degree centrality of all nodees at a distance of 1 from the node
total_reduced_degree_centrality=1
for neighbor in G.neighbors(node):
   total\_reduced\_degree\_centrality *= (1-nx.degree\_centrality(G)[neighbor]/max(nx.degree\_centrality(G).values())) \\
#calculate the percolation centralities
percolation_centrality=reduced_degree_centrality*total_reduced_degree_centrality
#Add the percolation centrality
\verb"percolation_centralities[node]="percolation_centrality" \\
print(percolation_centralities[node])
0.008040247300443136
#plt a histogram of the data
plt.hist(percolation_centralities.values(), bins=10,color='grey')
\# Add labels and a title to the plot
plt.xlabel('percolation centrality')
plt.ylabel('Yaxias')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True)
plt.title('Histogram of combined percolation centrality values for retweet')
\hbox{\#show the plot}
plt.show()
\overline{\mathbf{T}}
        Histogram of combined percolation centrality values for retweet
```

> Spring Layouts

-0.4

-0.2

0.0

percolation centrality

0.2

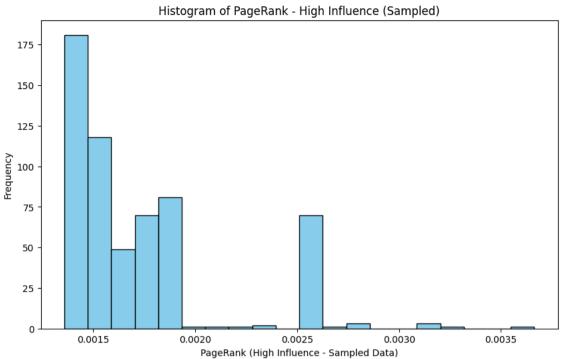
0.4

[] L, 4 cells hidden

PageRank

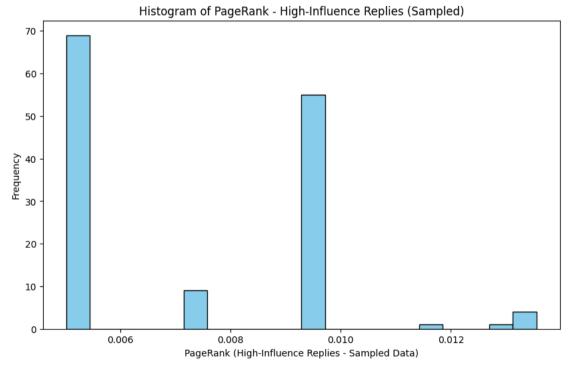
```
import random
import networkx as nx
import pandas as pd
import matplotlib.pyplot as plt
\mbox{\tt\#} Input and output file paths
input_file = '/content/drive/My Drive/Colab Notebooks/cs131/highinfl_AdjList.tsv'
sampled_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_highinfl_AdjList.tsv'
\mbox{\tt\#} Step 1: Create a random 1% sample of the adjacency list
sampling_rate = 0.01
with open(input_file, 'r') as infile, open(sampled_file, 'w') as outfile:
    for line in infile:
       if random.random() < sampling_rate: # Keep 1% of lines randomly</pre>
           outfile.write(line)
print(f"Random sample saved to: {sampled_file}")
# Step 2: Load the sampled adjacency list into a NetworkX graph
G = nx.read_edgelist(sampled_file, delimiter='\t', create_using=nx.DiGraph())
# Step 3: Calculate PageRank
pagerank = nx.pagerank(G)
# Step 4: Plot histogram for PageRank
plt.figure(figsize=(10, 6))
plt.hist(pagerank.values(), bins=20, color='skyblue', edgecolor='black')
plt.xlabel('PageRank (High Influence - Sampled Data)')
plt.ylabel('Frequency')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True) # Ensure y-axis has integer ticks
plt.title('Histogram of PageRank - High Influence (Sampled)')
plt.show()
```

Random sample saved to: /content/drive/My Drive/Colab Notebooks/cs131/sampled_highinfl_AdjList.tsv



```
import random
import networkx as nx
import pandas as pd
import matplotlib.pyplot as plt
# Input and output file paths for high-influence replies
input_file = '/content/drive/My Drive/Colab Notebooks/cs131/replies_nobots_uniq_highinfluence.NONOUSER.txt'
sampled_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_highinfluence.txt'
# Step 1: Create a random 1% sample of the adjacency list
sampling_rate = 0.01
with open(input_file, 'r') as infile, open(sampled_file, 'w') as outfile:
    for line in infile:
       if random.random() < sampling_rate: # Keep 1% of lines randomly</pre>
           outfile.write(line)
print(f"Random sample saved to: {sampled_file}")
# Step 2: Load the sampled adjacency list into a NetworkX graph
G_high = nx.read_edgelist(sampled_file, delimiter='\t', create_using=nx.DiGraph())
# Step 3: Calculate PageRank
pagerank_high = nx.pagerank(G_high)
# Step 4: Save PageRank to a file
pagerank_df_high = pd.DataFrame(list(pagerank_high.items()), columns=['Node', 'PageRank'])
pagerank_df_high.to_csv('/content/drive/My Drive/Colab Notebooks/cs131/pagerank_sampled_high_replies.tsv', sep='\t', index=False)
# Step 5: Plot histogram for PageRank
plt.figure(figsize=(10, 6))
plt.hist(pagerank_high.values(), bins=20, color='skyblue', edgecolor='black')
plt.xlabel('PageRank (High-Influence Replies - Sampled Data)')
plt.ylabel('Frequency')
plt.title('Histogram of PageRank - High-Influence Replies (Sampled)')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True) # Ensure y-axis has integer ticks
plt.show()
```

Random sample saved to: /content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_highinfluence.txt

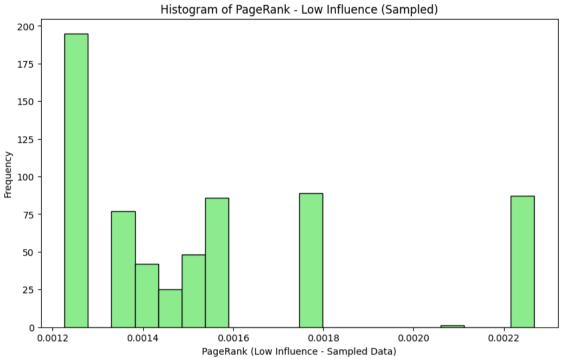


```
# Step 2: Load the sampled adjacency list into a NetworkX graph
G = nx.read_edgelist(sampled_file, delimiter='\t', create_using=nx.DiGraph())

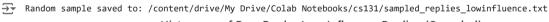
# Step 3: Calculate PageRank
pagerank = nx.pagerank(G)

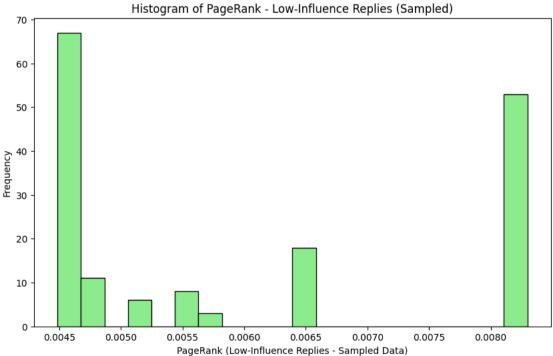
# Step 4: Plot histogram for PageRank
plt.figure(figsize=(10, 6))
plt.hist(pagerank.values(), bins=20, color='lightgreen', edgecolor='black')
plt.xlabel('PageRank (Low Influence - Sampled Data)')
plt.ylabel('Frequency')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True)  # Ensure y-axis has integer ticks
plt.title('Histogram of PageRank - Low Influence (Sampled)')
plt.show()
```

Random sample saved to: /content/drive/My Drive/Colab Notebooks/cs131/sampled_lowinfl_AdjList.tsv



```
# Input and output file paths for low-influence replies
input_file = '/content/drive/My Drive/Colab Notebooks/cs131/replies_nobots_uniq_lowinfluence.NONOUSER.txt'
sampled_file = '/content/drive/My Drive/Colab Notebooks/cs131/sampled_replies_lowinfluence.txt'
# Step 1: Create a random 1% sample of the adjacency list
sampling_rate = 0.01
with open(input_file, 'r') as infile, open(sampled_file, 'w') as outfile:
    for line in infile:
       if random.random() < sampling_rate: # Keep 1% of lines randomly</pre>
            outfile.write(line)
print(f"Random sample saved to: {sampled_file}")
# Step 2: Load the sampled adjacency list into a NetworkX graph
G_low = nx.read_edgelist(sampled_file, delimiter='\t', create_using=nx.DiGraph())
# Step 3: Calculate PageRank
pagerank_low = nx.pagerank(G_low)
# Step 4: Save PageRank to a file
pagerank_df_low = pd.DataFrame(list(pagerank_low.items()), columns=['Node', 'PageRank'])
pagerank\_df\_low.to\_csv('\underline{/content/drive/My\ Drive/Colab}\ Notebooks/cs131/pagerank\_sampled\_low\_replies.tsv',\ sep='\t',\ index=False)
# Step 5: Plot histogram for PageRank
plt.figure(figsize=(10, 6))
plt.hist(pagerank_low.values(), bins=20, color='lightgreen', edgecolor='black')
plt.xlabel('PageRank (Low-Influence Replies - Sampled Data)')
plt.ylabel('Frequency')
plt.title('Histogram of PageRank - Low-Influence Replies (Sampled)')
plt.gca().get_yaxis().get_major_locator().set_params(integer=True) # Ensure y-axis has integer ticks
plt.show()
```





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