
Network Science for Web(DS608)-Final Project

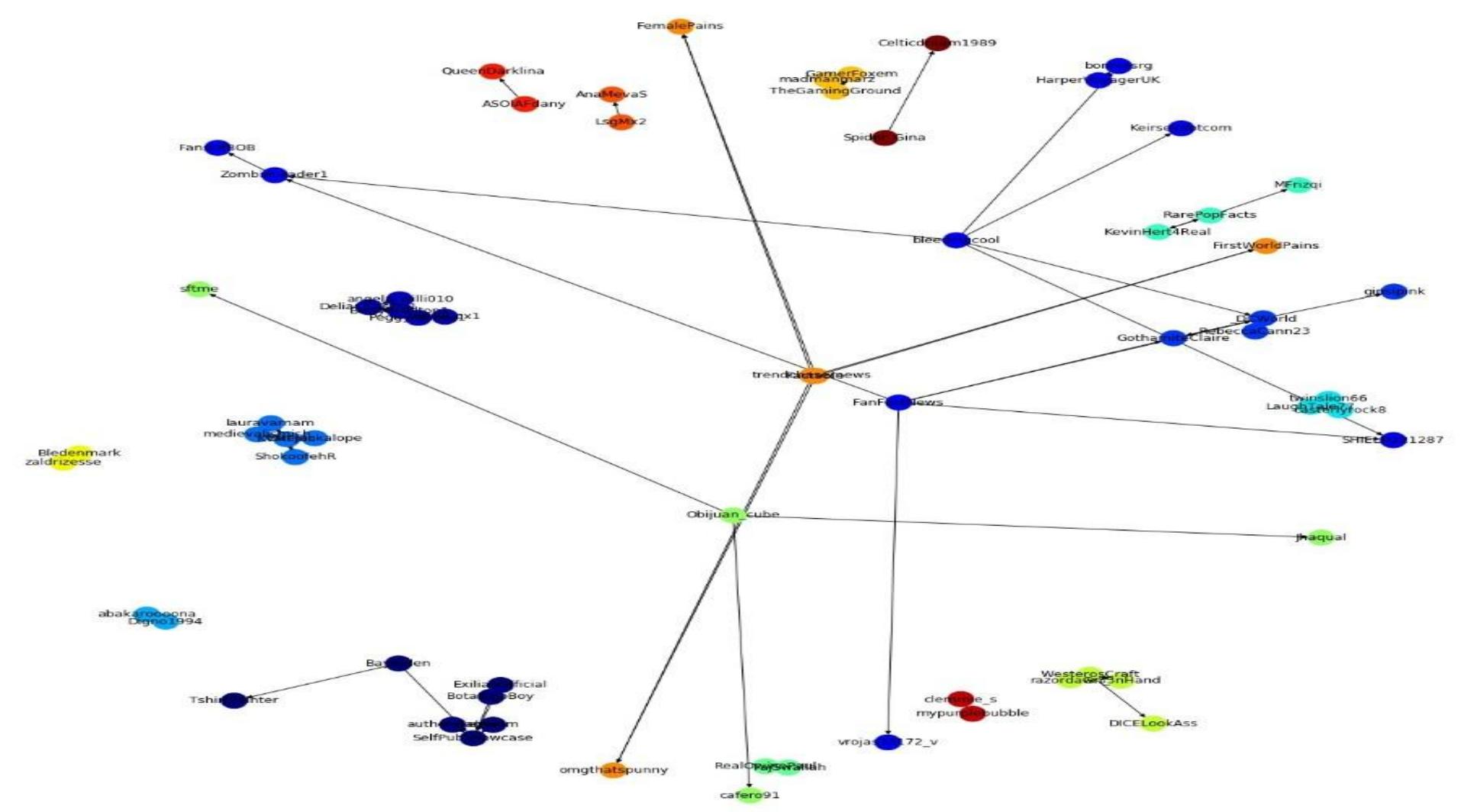
Group Members

1. Lokesh Garg(MT2018053)
2. Sagar Jhunjhunwala(MT2018097)
3. Shubham Darokar(MT2018113)
4. Vivek Gupta(MT2018134)
5. Apurva Kulkarni(PH2018020)

Follower-Followee Network for GOT

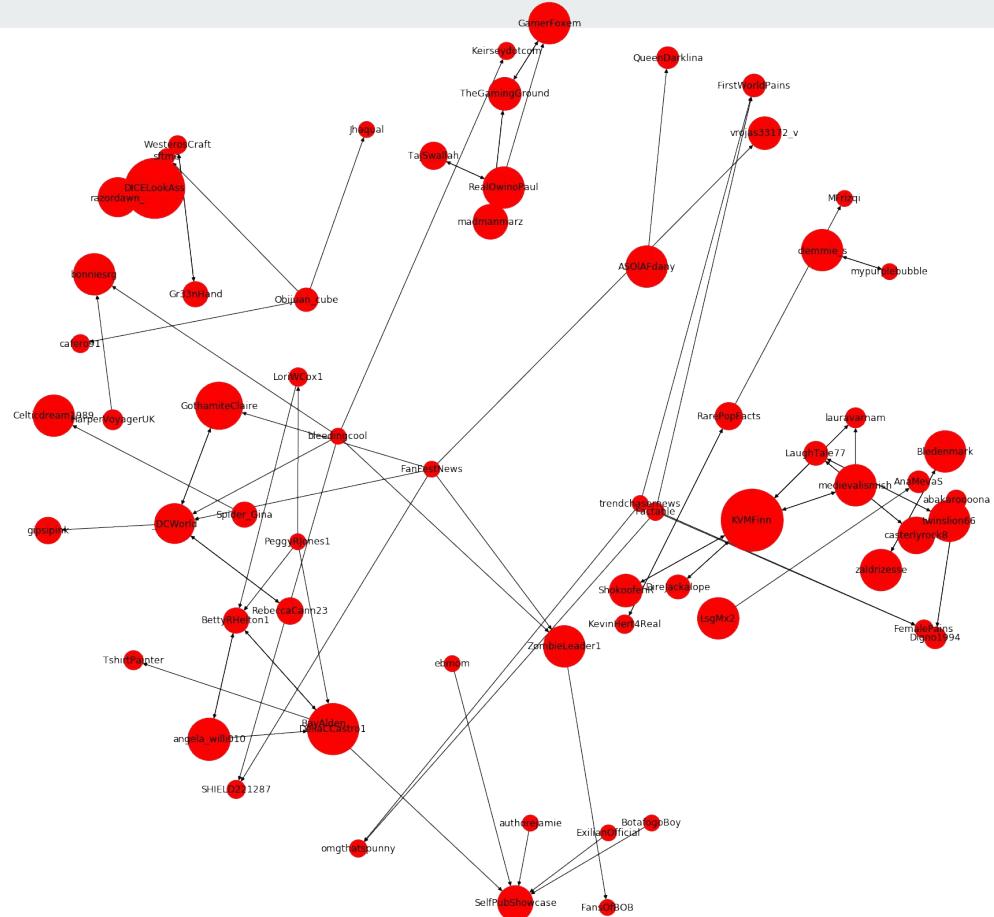


- Number of nodes: 66
- Number of edges: 81



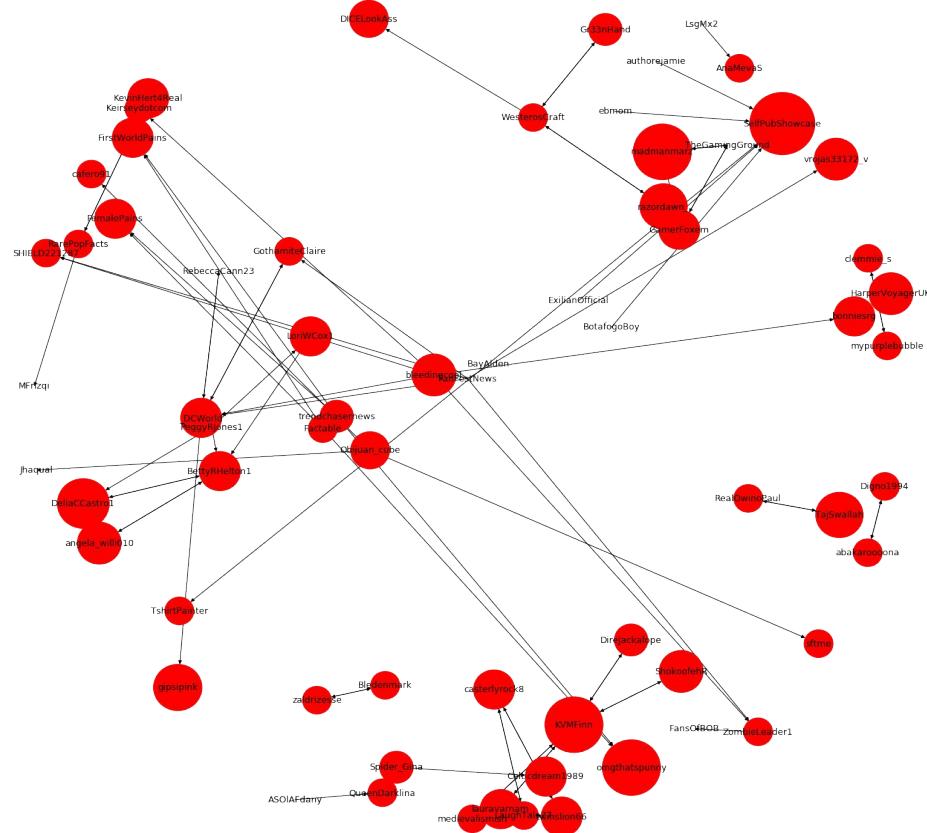
Page Rank:

PageRank works by counting the number and quality of edges to a node to determine a rough estimate of how important the node is. The underlying assumption is that more important nodes are likely to receive more links from other nodes.



Closeness:

In a connected graph, closeness centrality (or closeness) of a node is a measure of centrality in a network, calculated as the reciprocal of the sum of the length of the shortest paths between the node and all other nodes in the graph. Thus, the more central a node is, the *closer* it is to all other nodes.

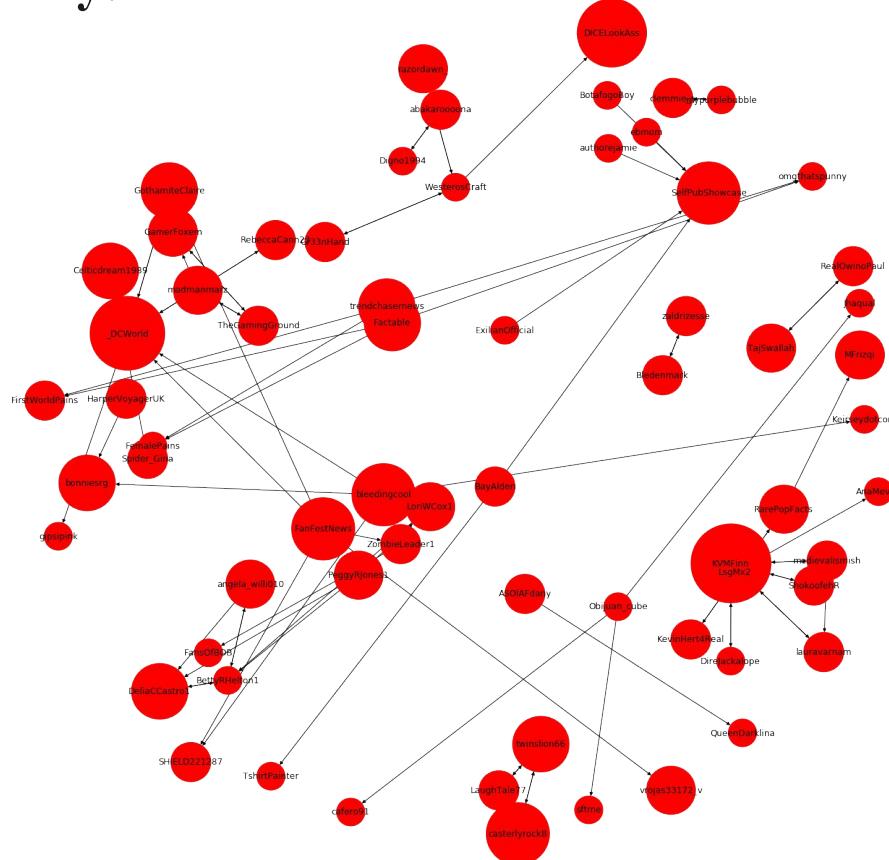


Betweenness:

Betweenness is a centrality measure of a vertex within a graph. Betweenness centrality quantifies the number of times a node acts as a bridge along the shortest path between two other nodes.

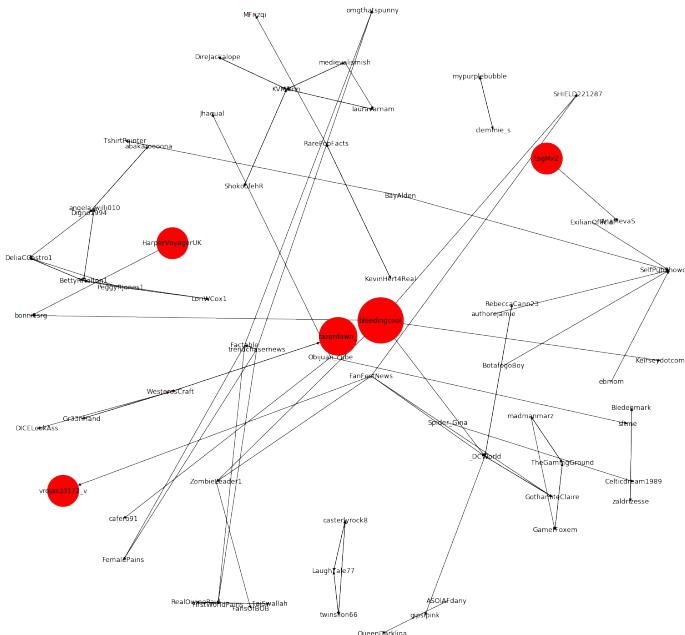


Degree Centrality:



Eigen Vector:

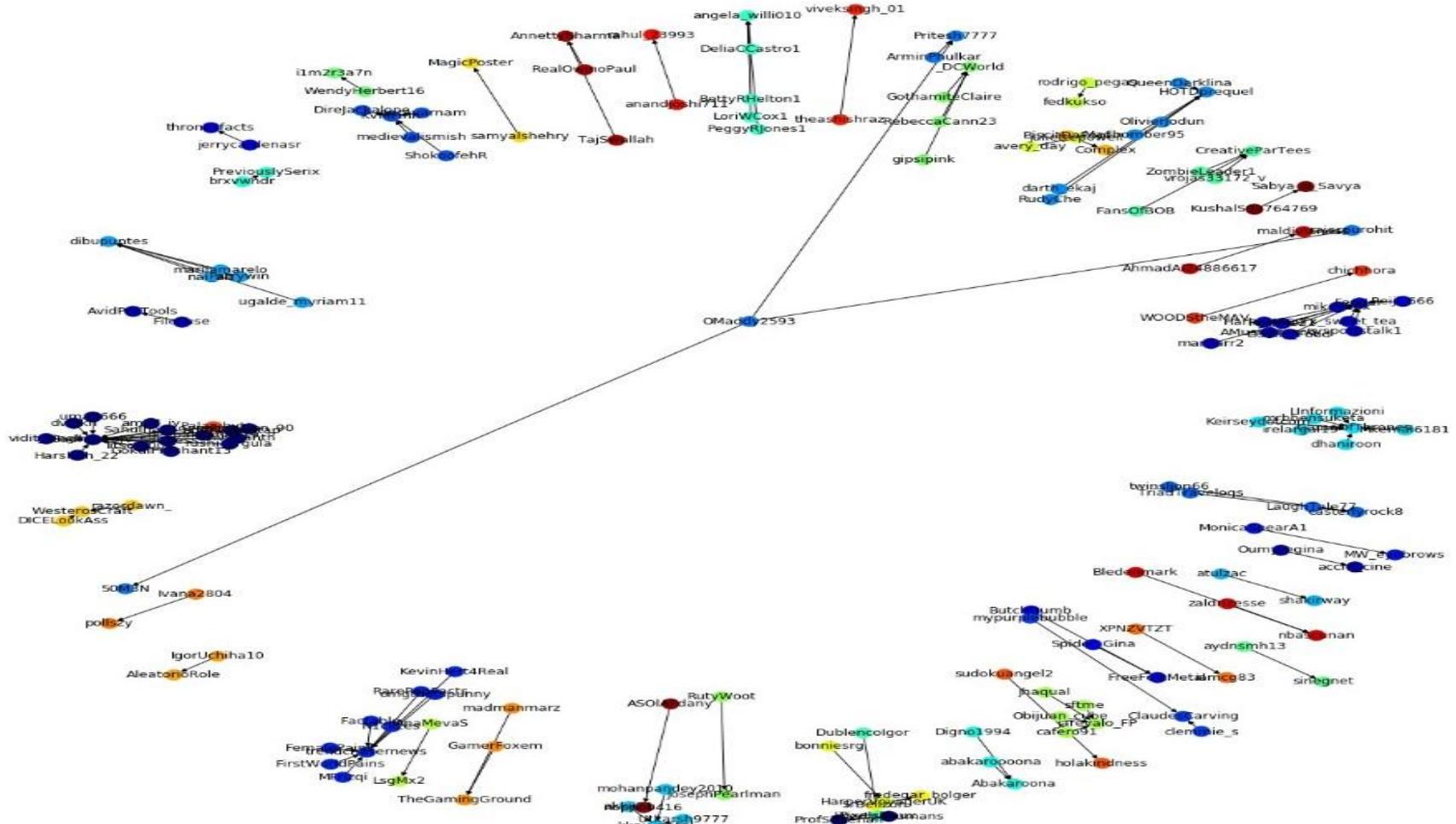
Eigenvector centrality is a measure of the influence a node has on a network. If a node is pointed to by many nodes then that node will have high eigenvector centrality.



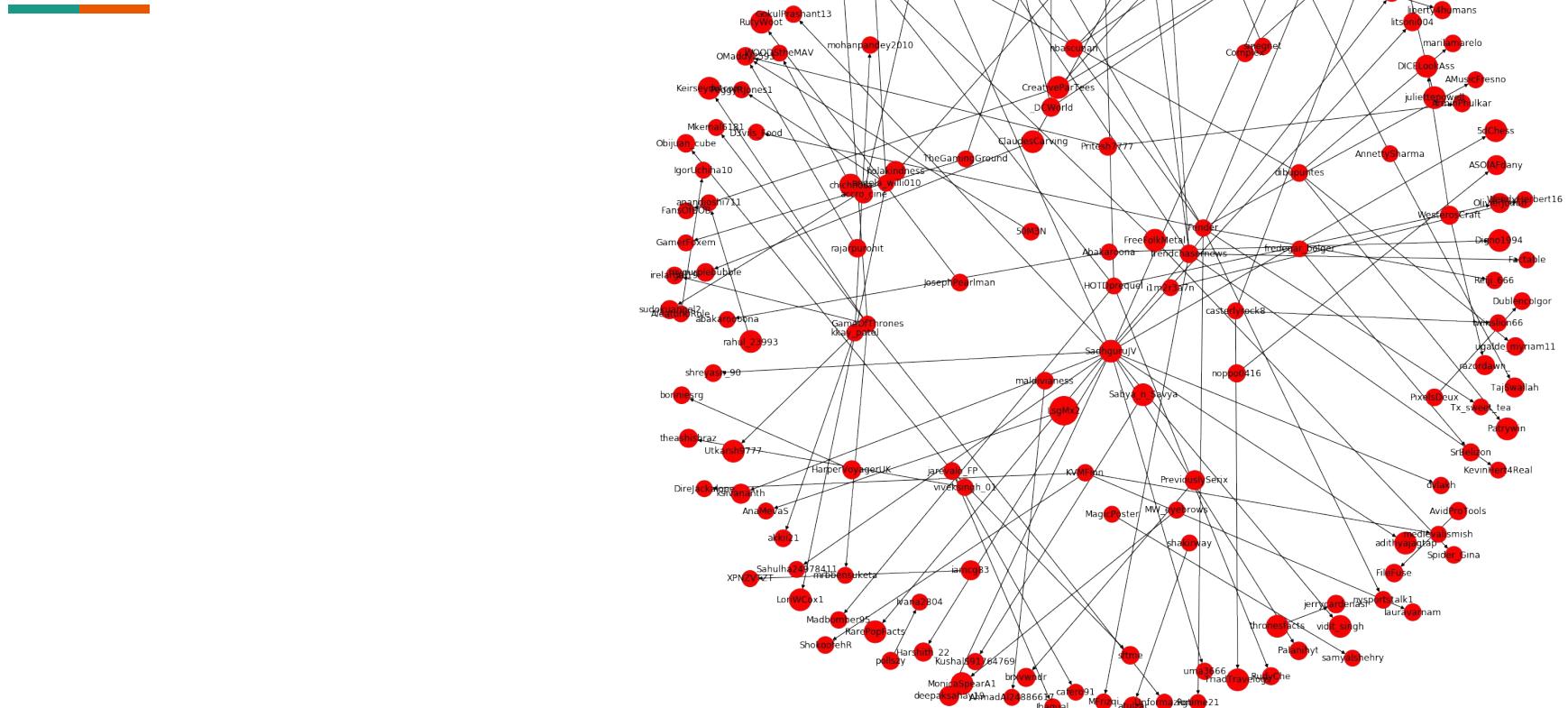
Retweet Graph for GOT:



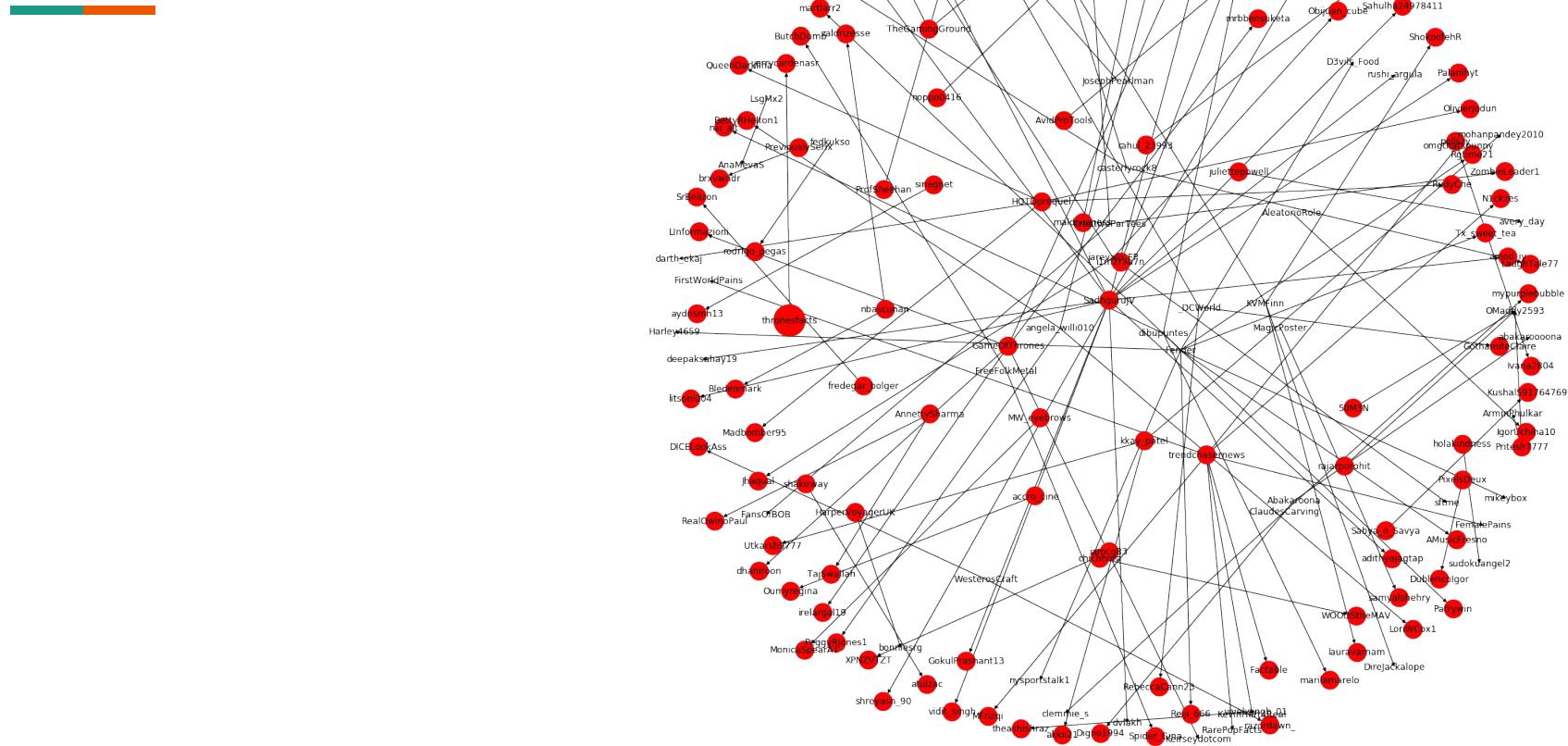
- Number of nodes: 166
- Number of edges: 117



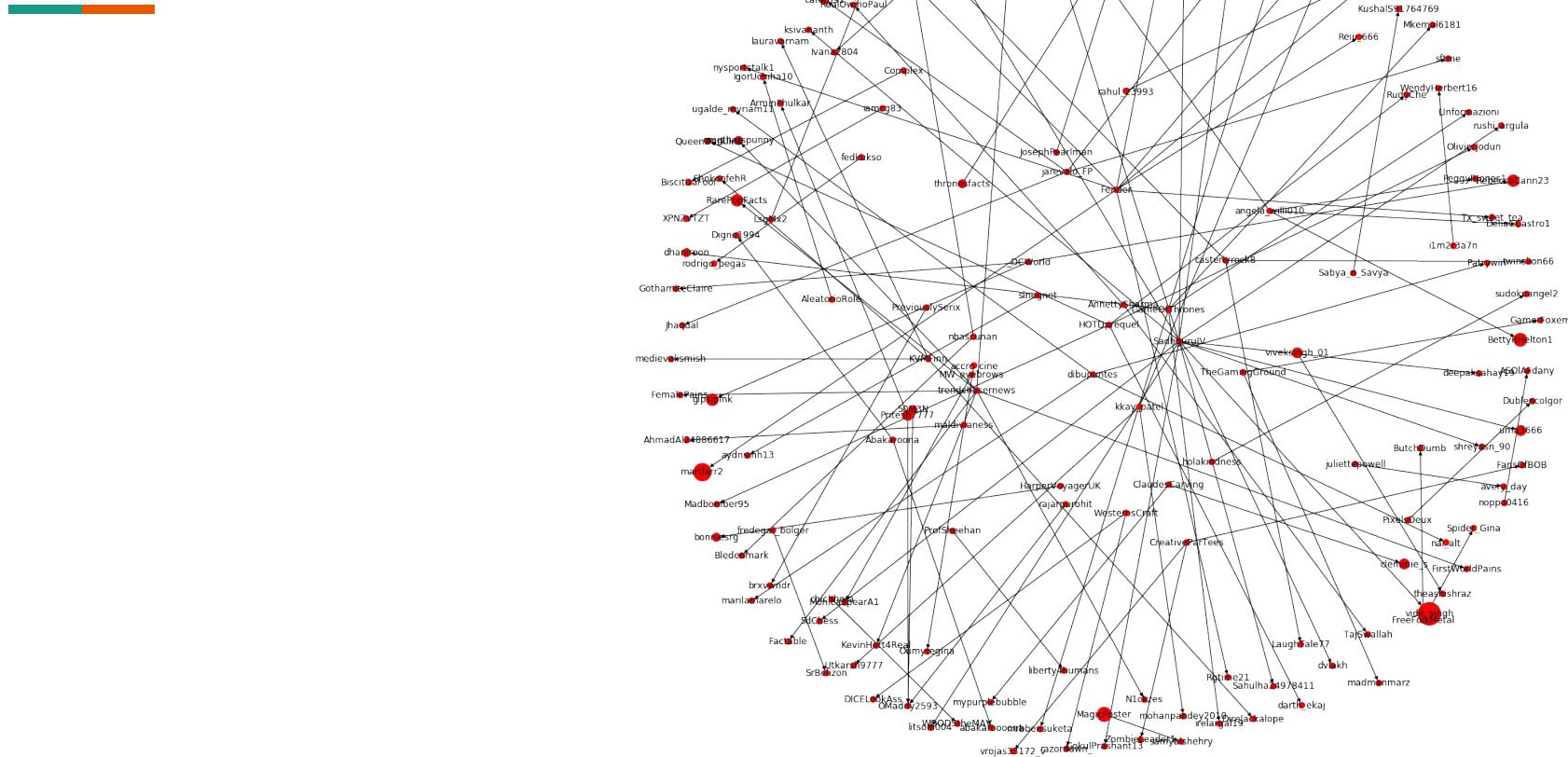
Page Rank:



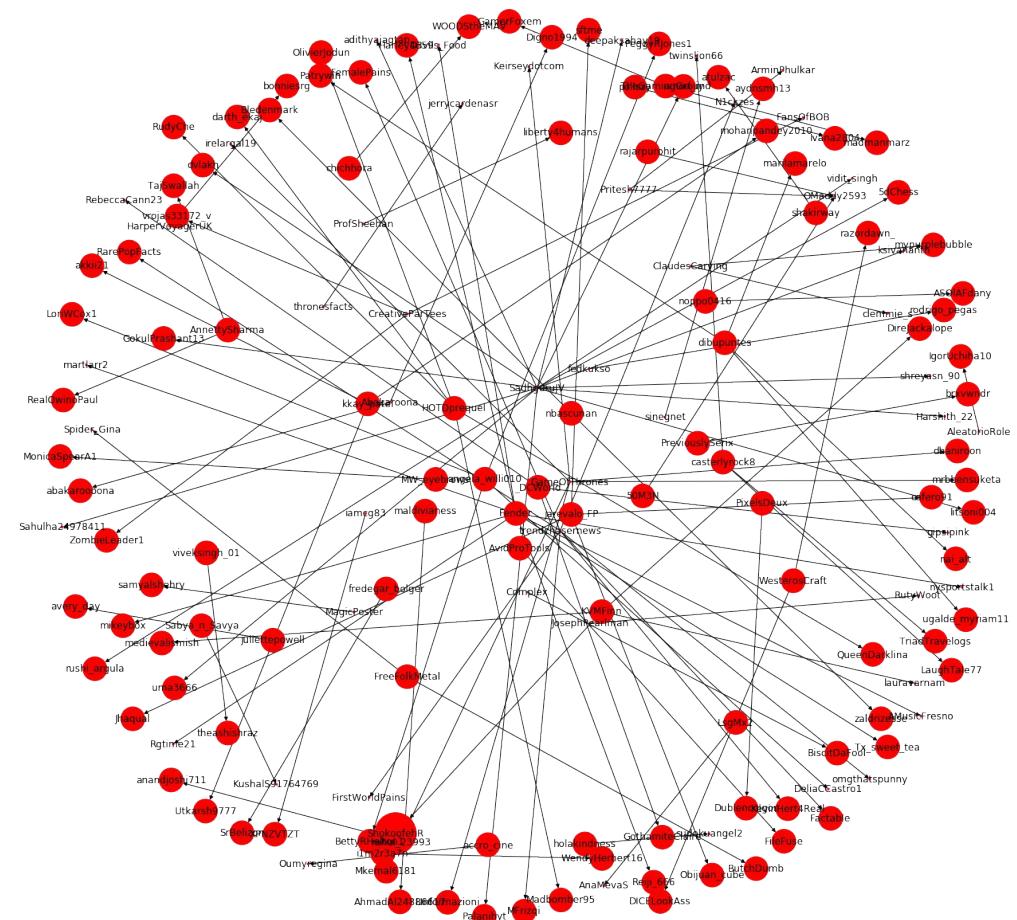
Closeness:



Degree Centrality:



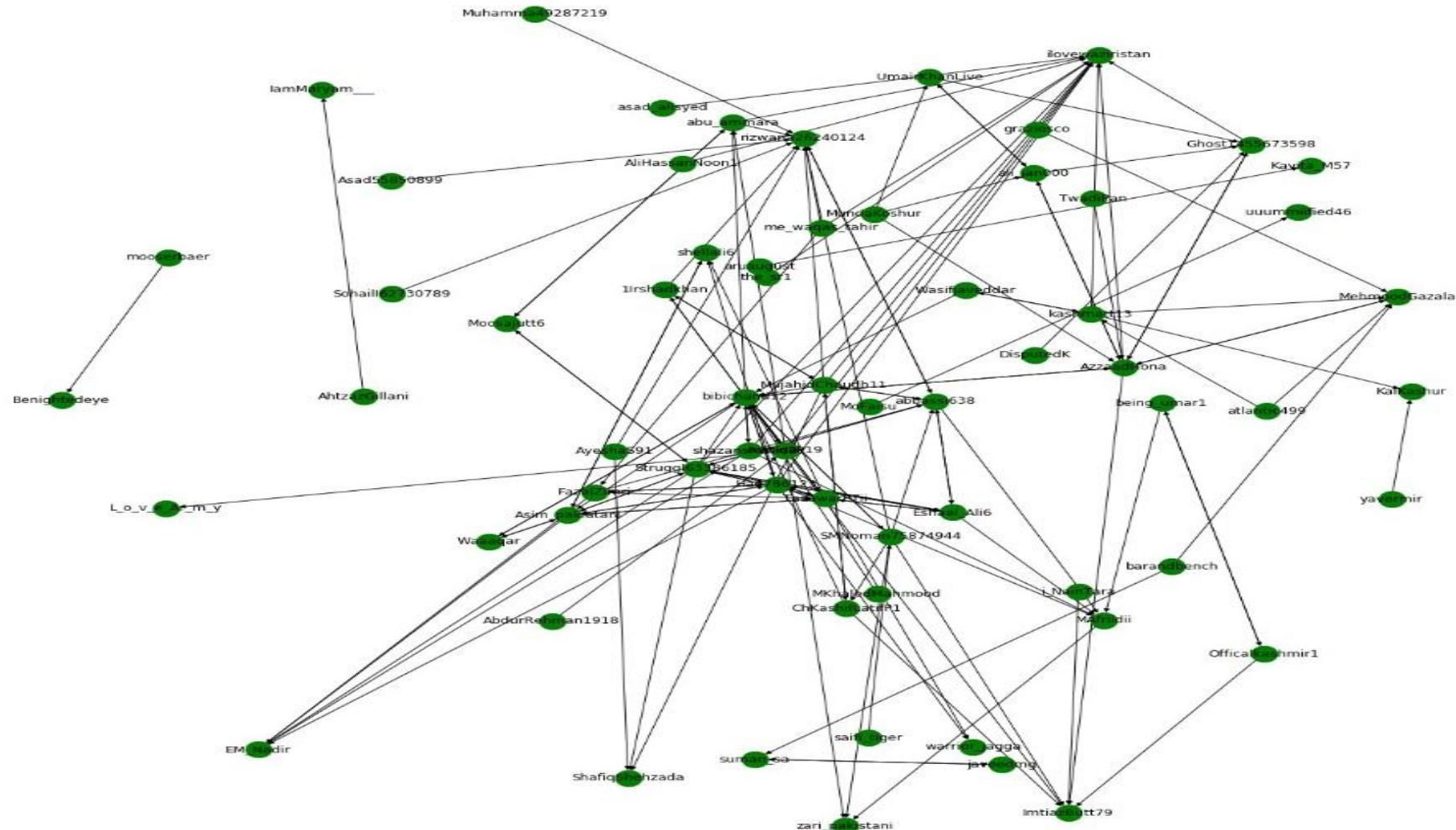
Eigen Vector:



Follower Followee for Kashmir:

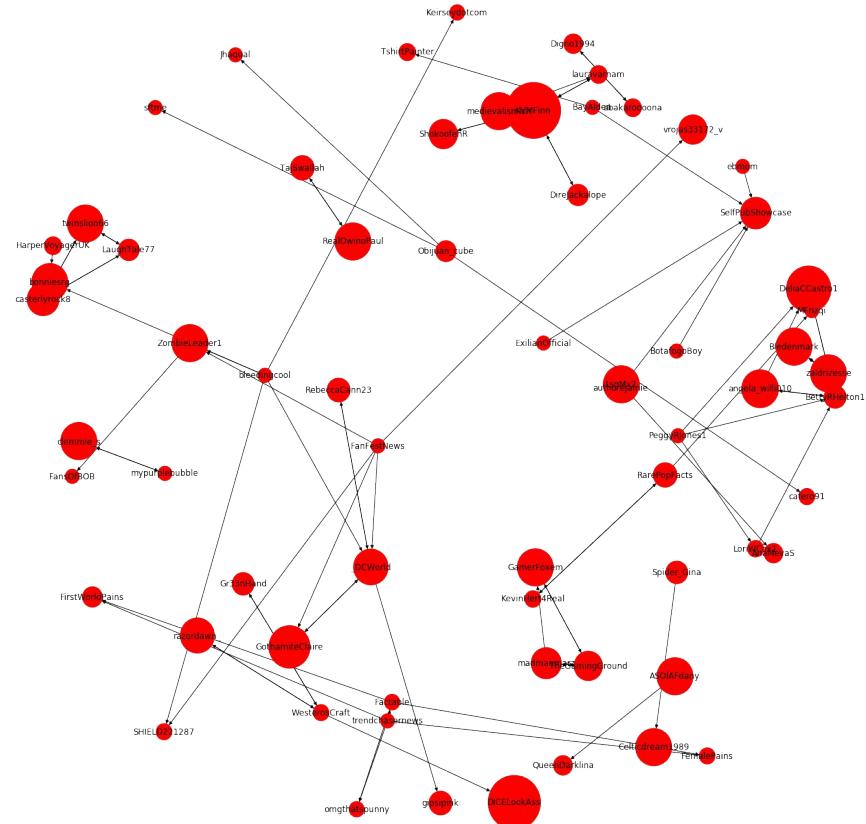


- Number of nodes: 66
- Number of edges: 152



Page Rank:

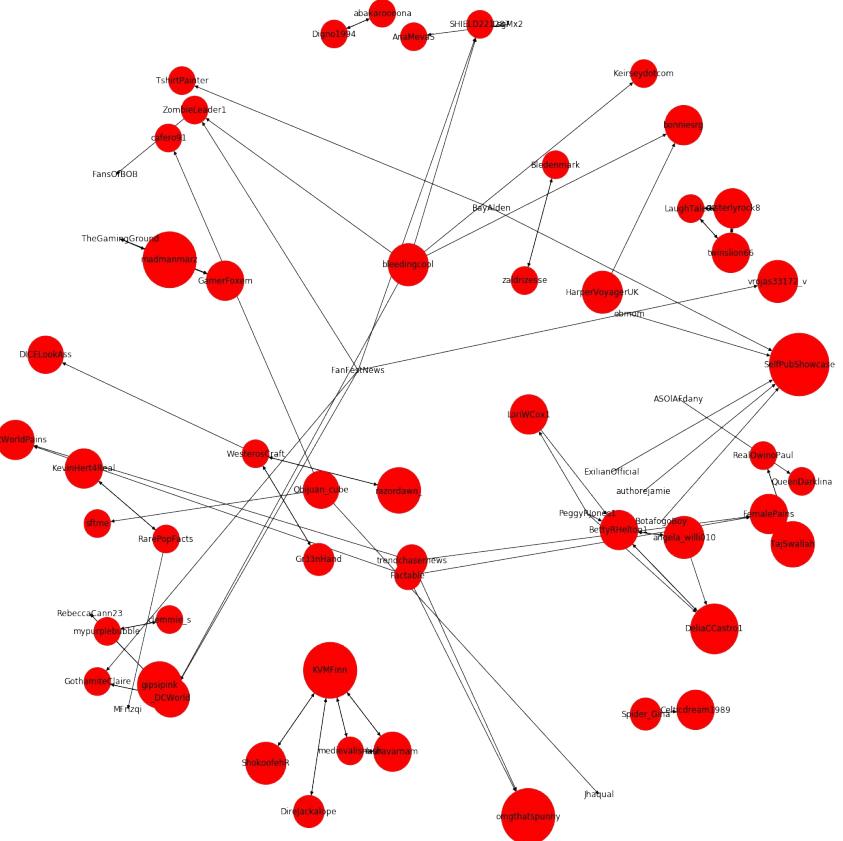
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Closeness:

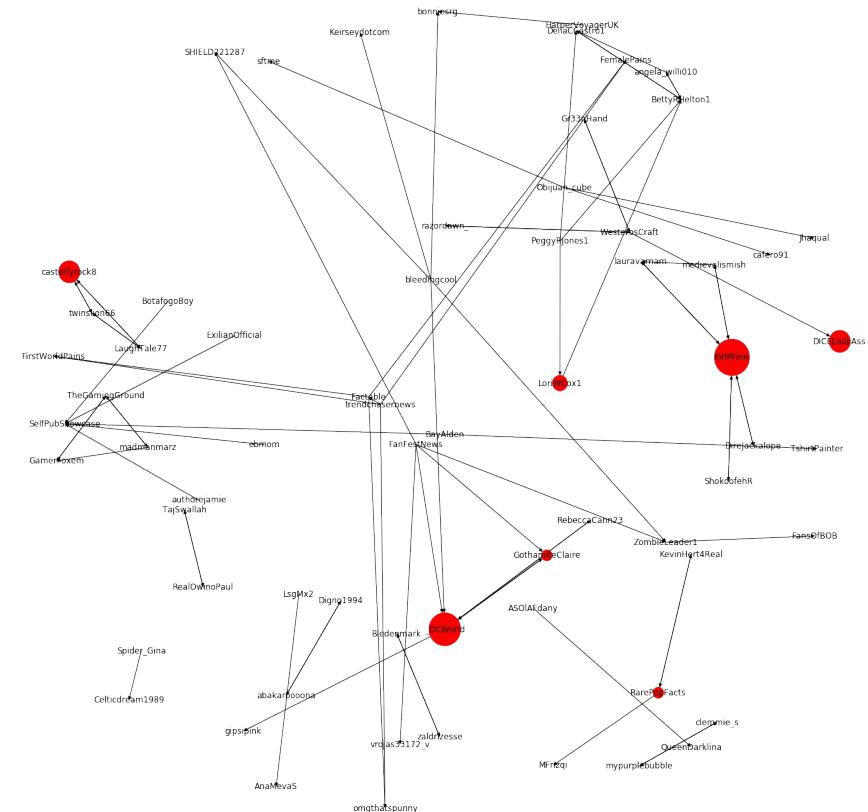


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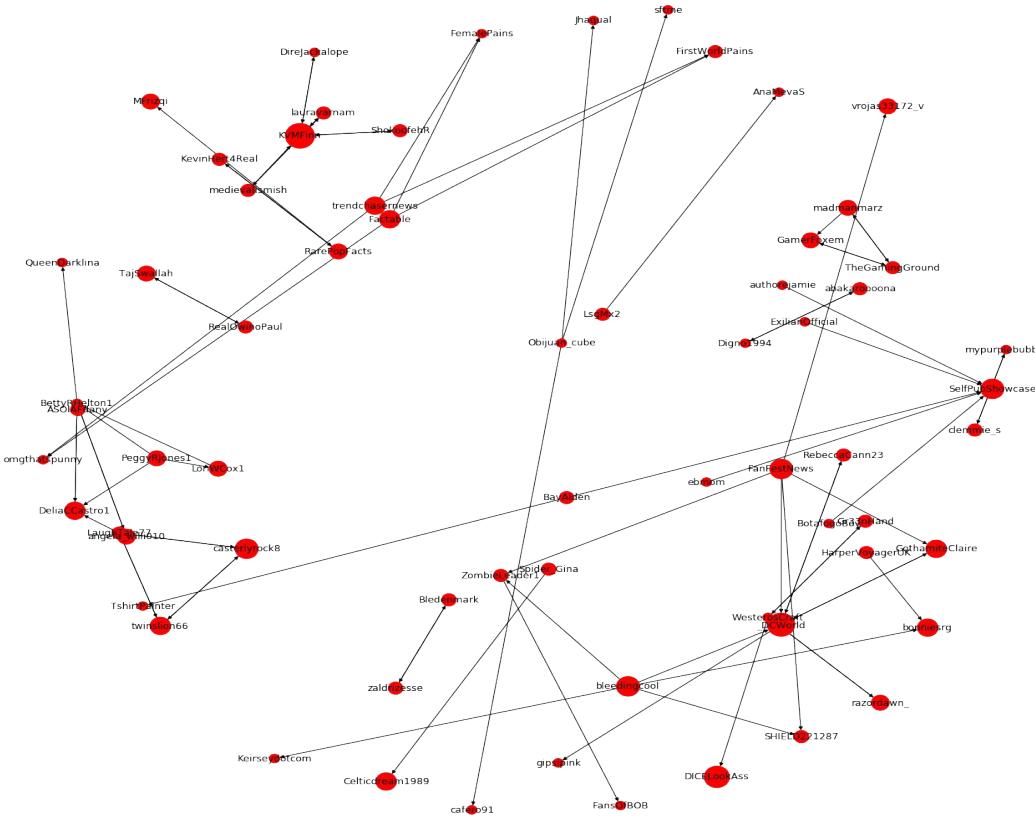


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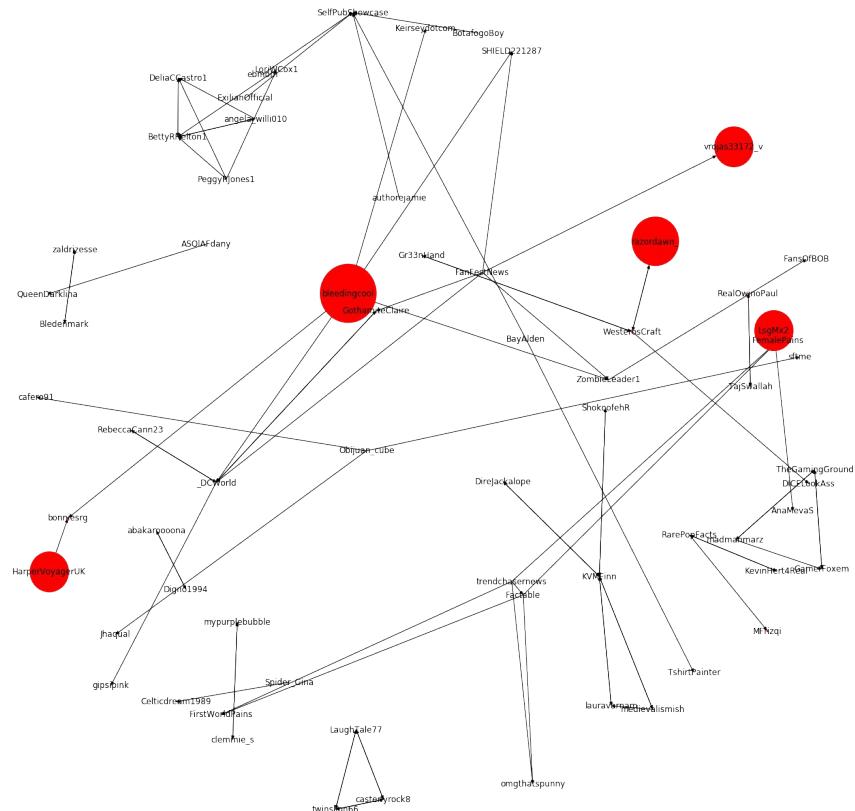


Degree:



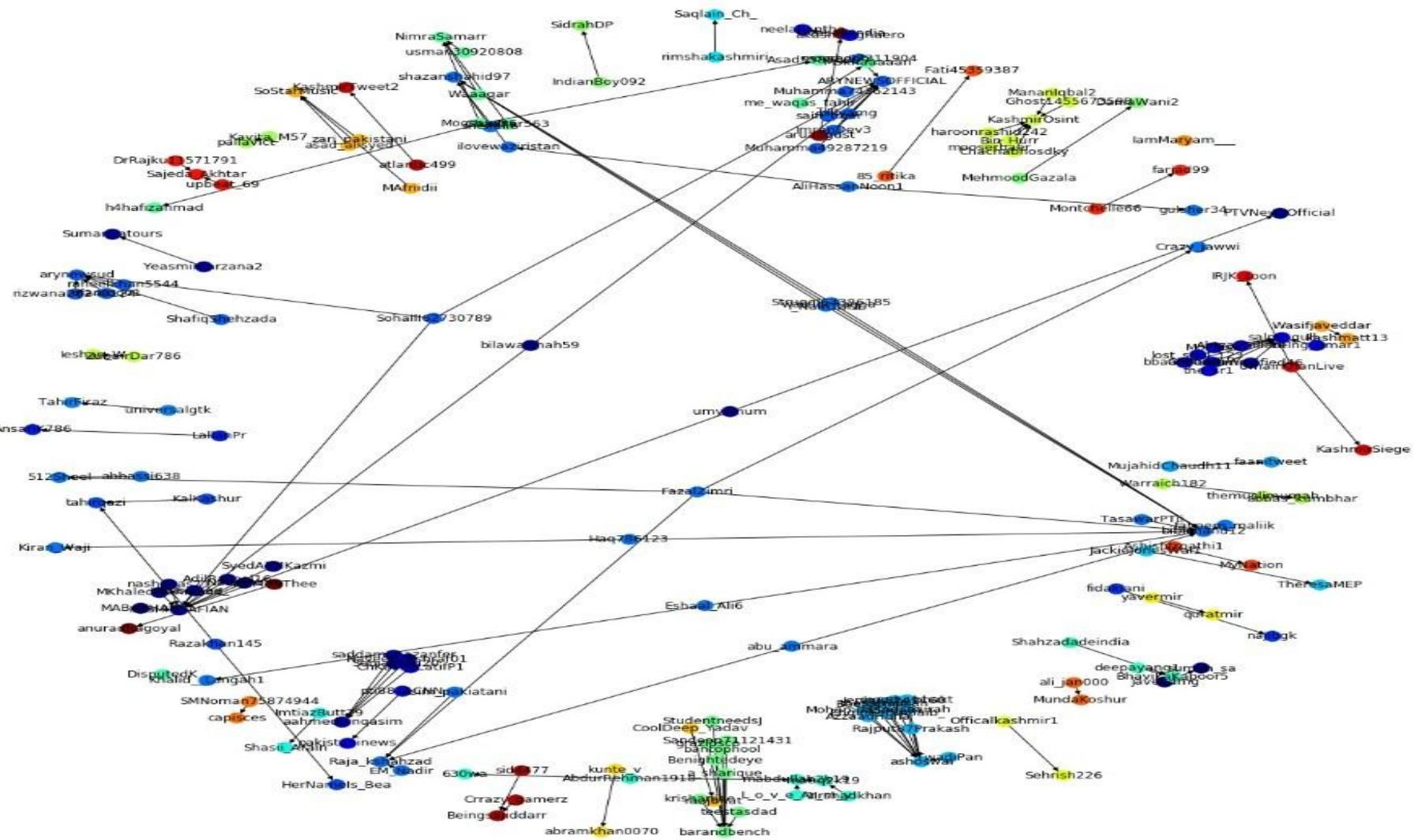
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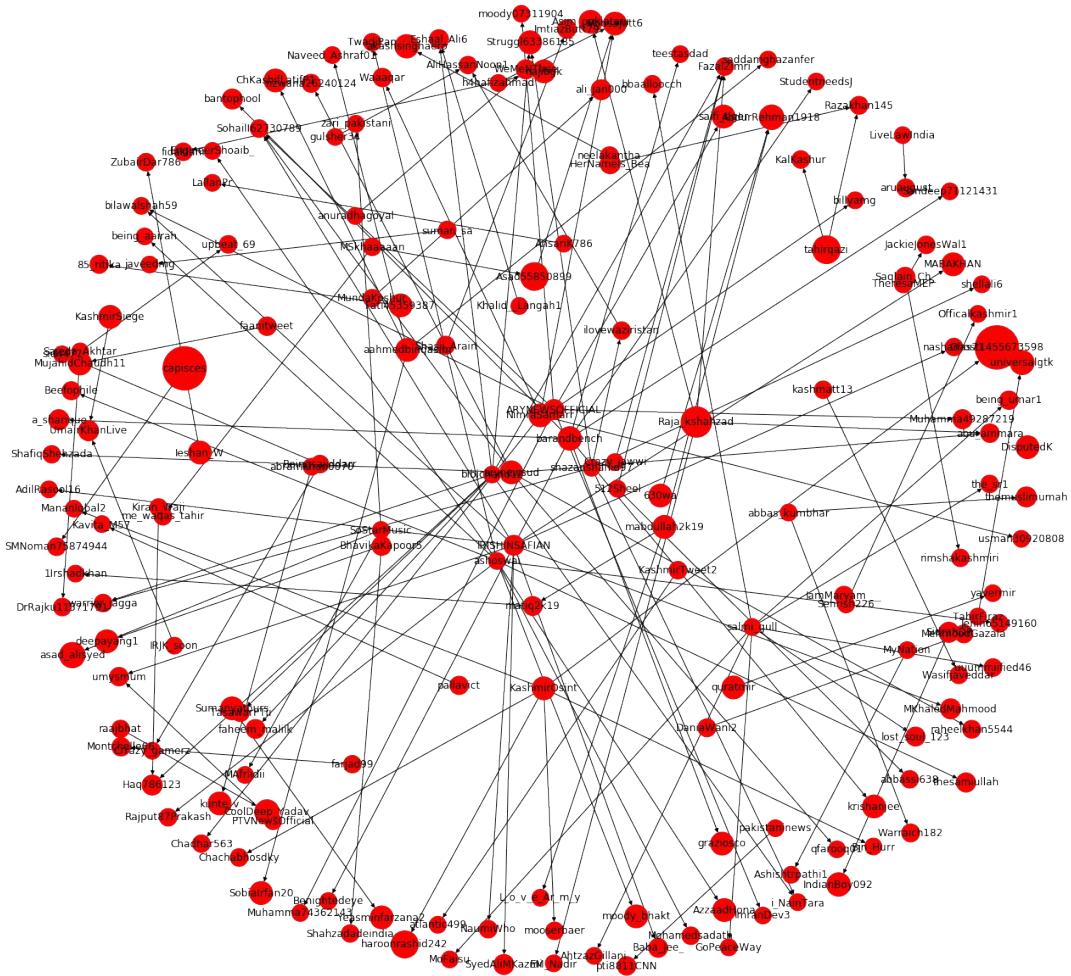


Retweet Graph for Kashmir:

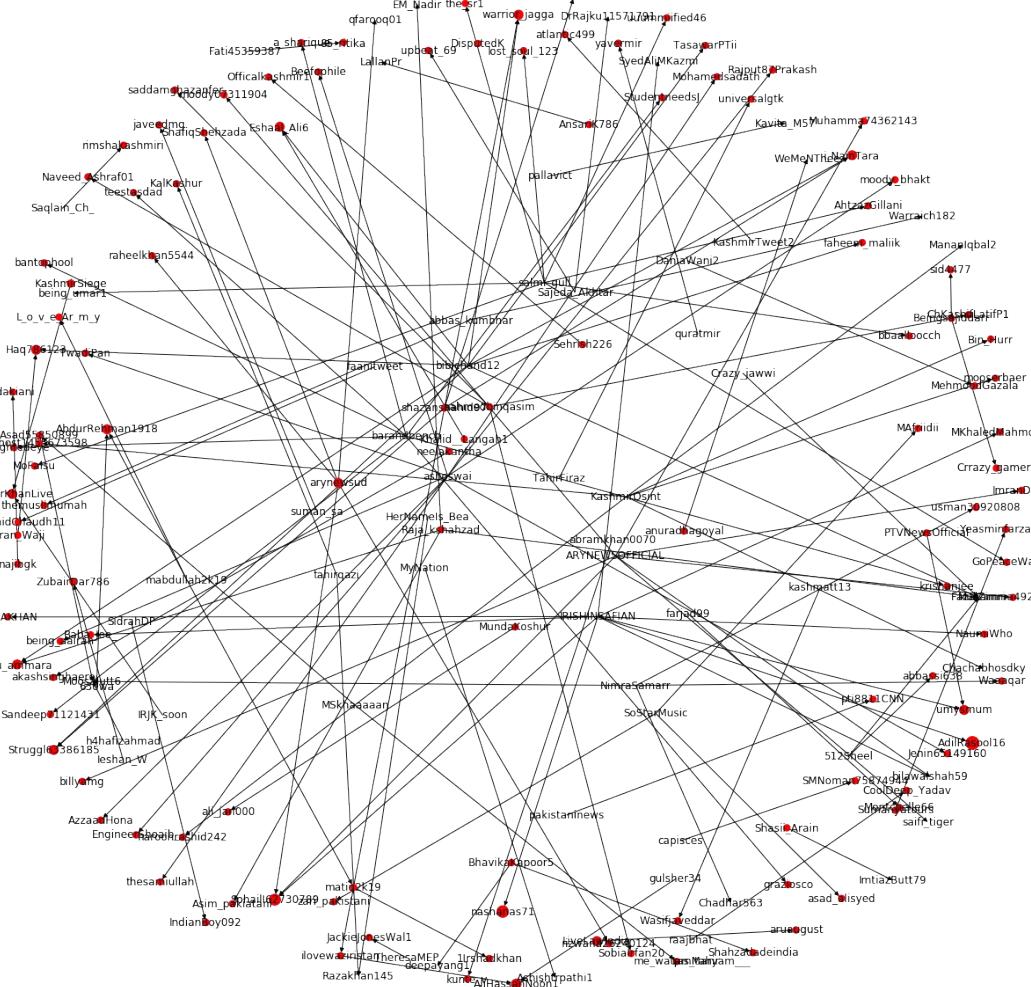
- Number of Nodes : 184
- Number of edges : 145



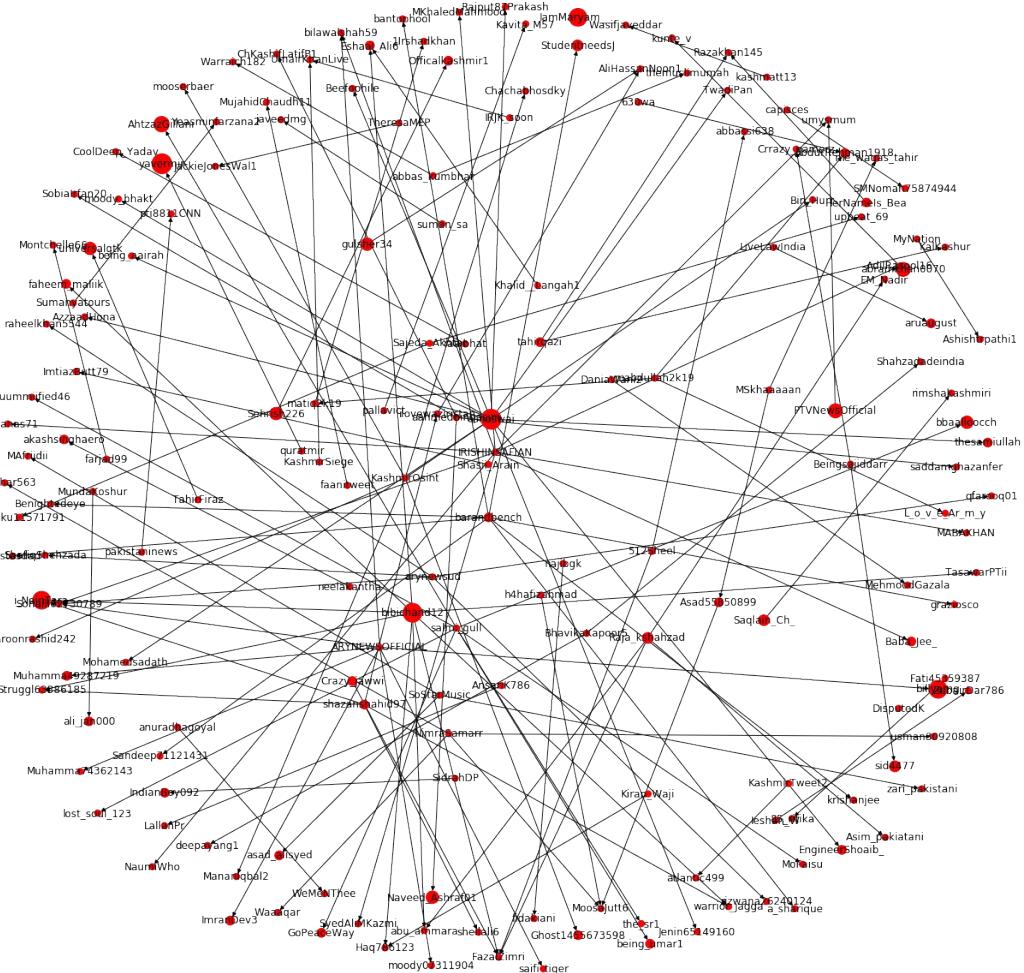
Page Rank:



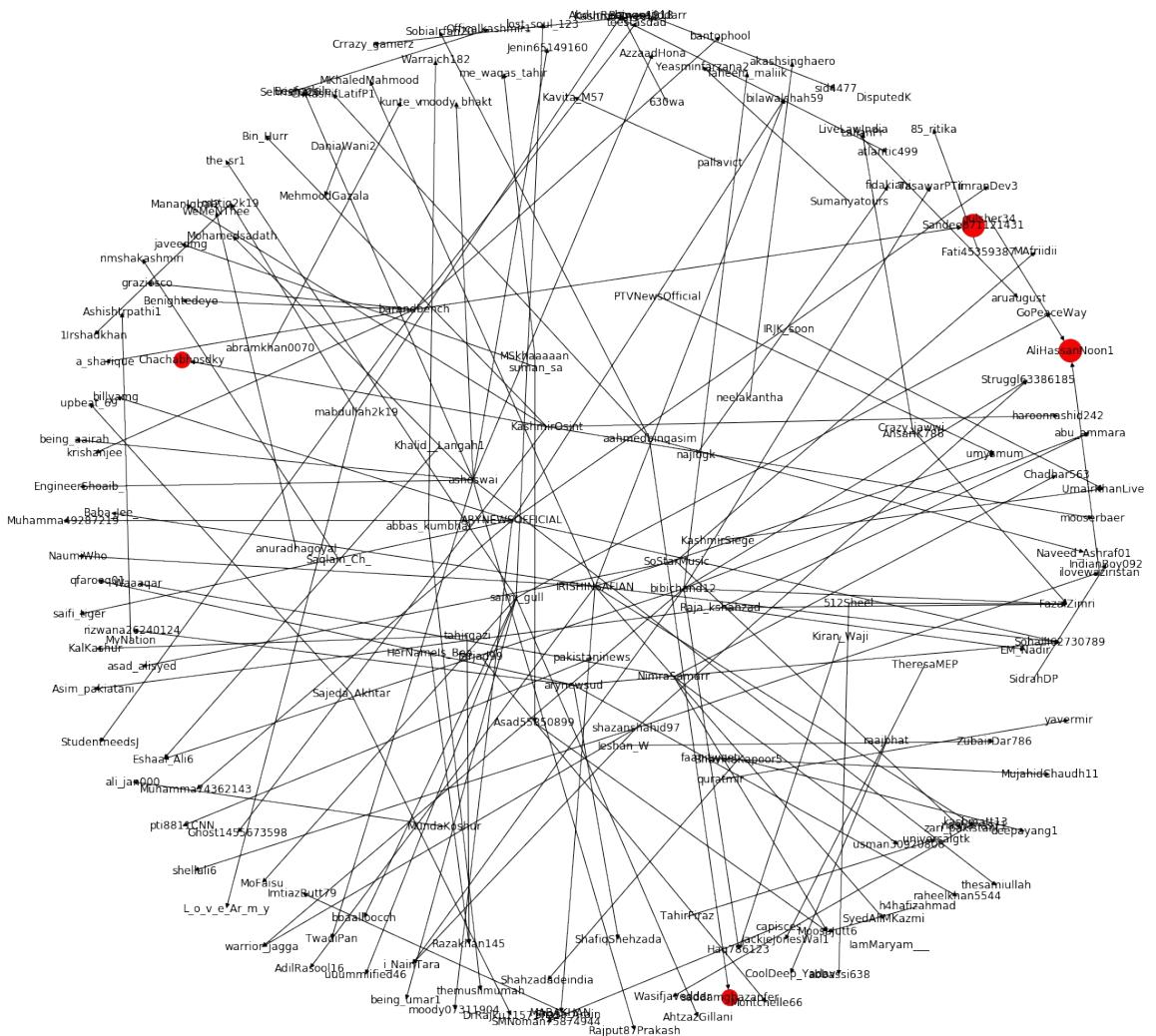
Closeness:



Degree:



Eigen Vector:

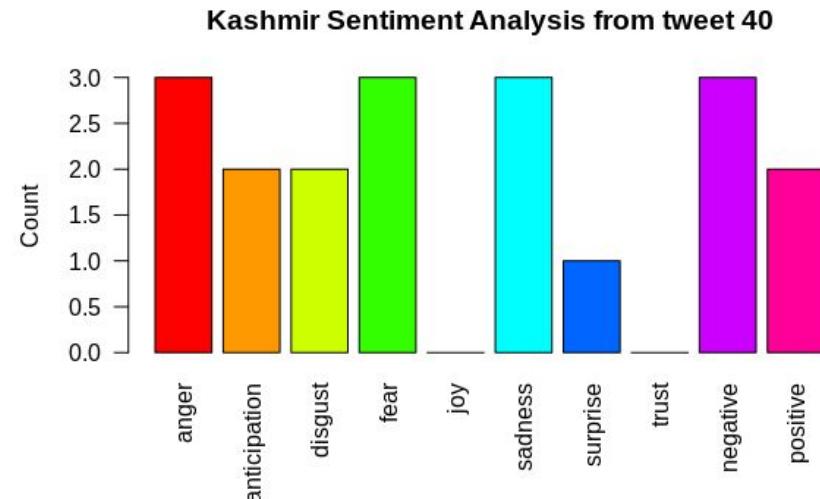


Part 2: Is there is shift in the sentiment over time?

- Kashmir Dataset

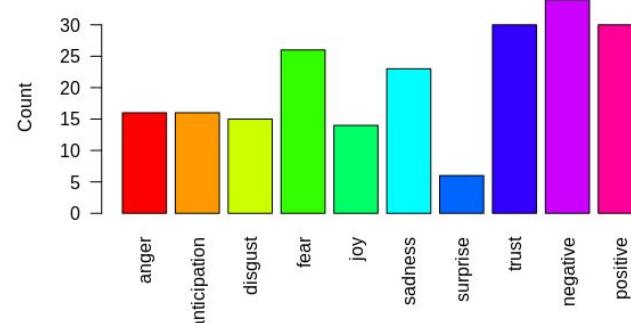
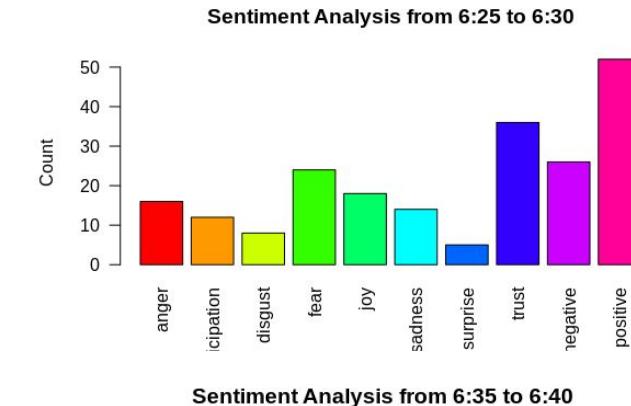
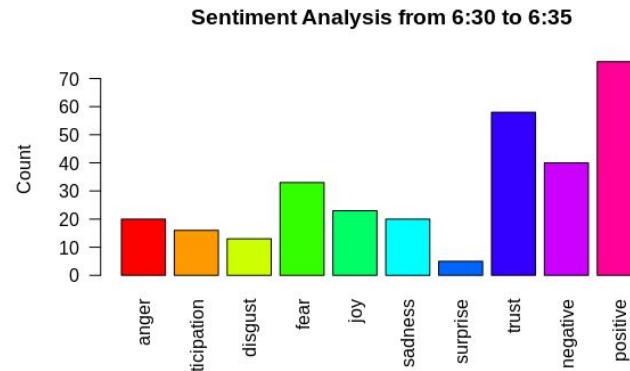
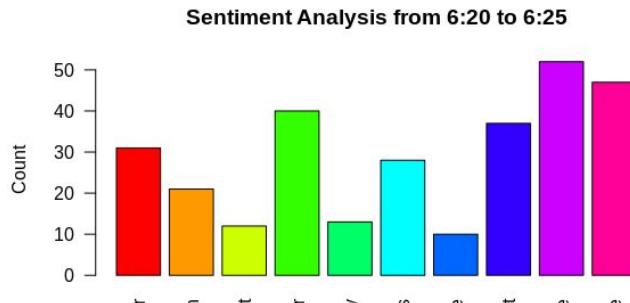
#Kashmir—Day 95

- Internet blocked
- Pre-paid mobile services blocked
- Businesses partially-closed, Rs 11k crore loss
- Schools/Colleges deserted
- Public transport off roads
- IT sector dead
- Tourism down by 85%
- 100k job losses
- 1000s in jails, untraceable
- Mental distress on rise



Part 2: Is there is shift in the sentiment over time?

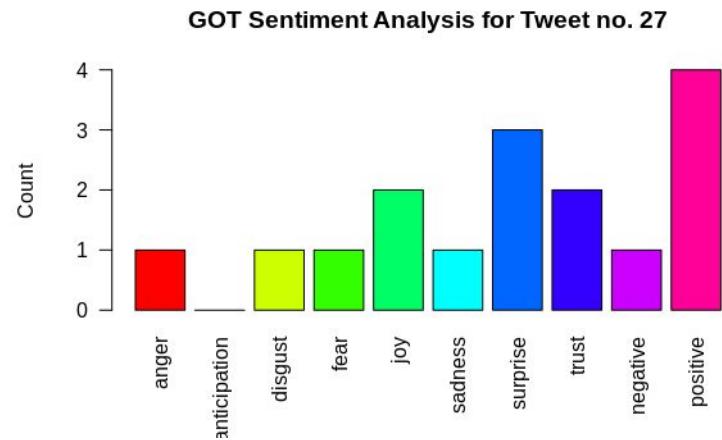
- Kashmir Dataset



Part 2: Is there is shift in the sentiment over time?

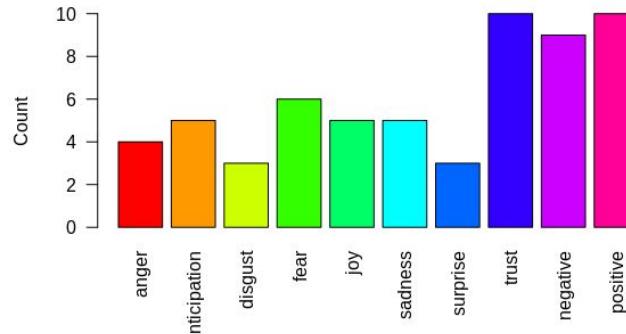
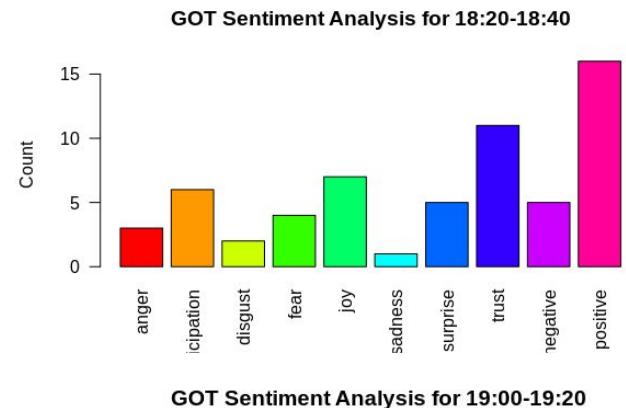
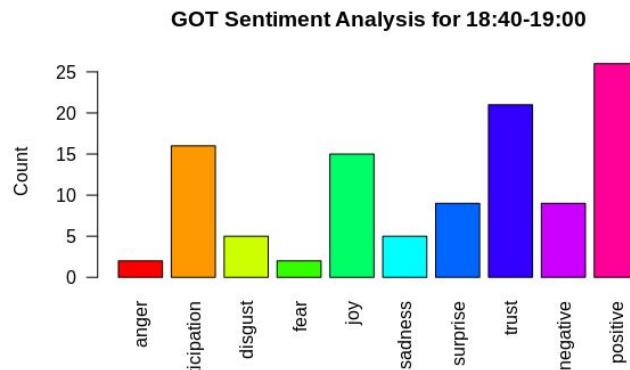
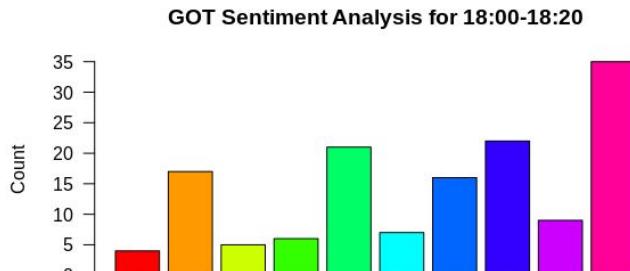
- GameOfThrones Dataset

"Do u love #Sales? We got a huge 1 for ya! If u r a
fan of #TheWalkingDead #GameOfThrones
#StrangerThings #Arrow #Flash #Marvel
#HarryPotter #Horror #DoctorWho and more,
don't miss our inventory reduction sale on designs
inspired by our favs in #POPCulture
#SupportSmallBusiness <https://t.co/eCTNl26y2F>"



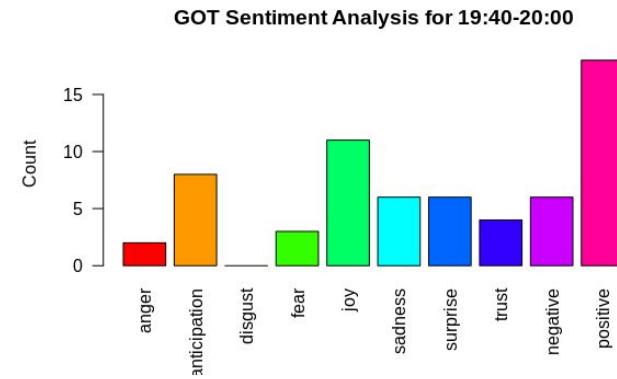
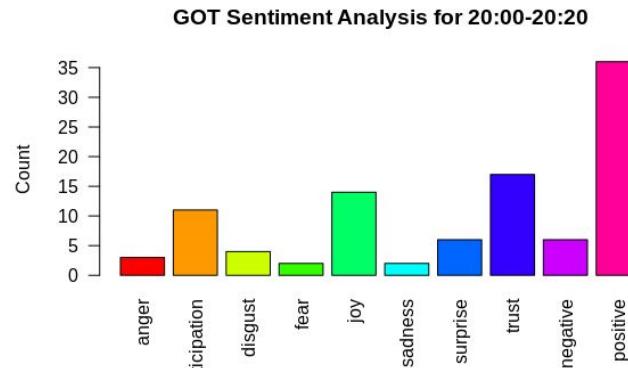
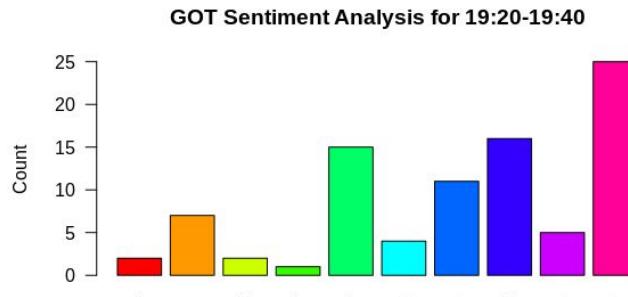
Part 2: Is there is shift in the sentiment over time?

- GameOfThrones Dataset



Part 2: Is there is shift in the sentiment over time?

- GameOfThrones Dataset



Is there any observable social learning over sentiments expressed ?

Degroot model: Take a society of agents where everybody has an opinion on a subject, represented by a vector of probabilities . Agents obtain no new information based on which they can update their opinions but they communicate with other agents. Links between agents (who knows whom) and the weight they put on each other's opinions is represented by a trust matrix T . Formally, the beliefs are updated in each period as

$$p(t) = Tp(t - 1)$$

Results for Kashmir dataset:

- Initial opinions:

```
array([-1.25000000e-01,  0.00000000e+00,  0.00000000e+00,  0.00000000e+00,
       0.00000000e+00,  0.00000000e+00,  1.34615385e-01,  0.00000000e+00,
      -5.35714286e-02,  0.00000000e+00,  0.00000000e+00,  0.00000000e+00,
       1.27500000e-01,  0.00000000e+00,  0.00000000e+00,  0.00000000e+00,
```

- Change in opinions:

```
[ 0.          0.05338542  0.015        0.21        0.21        0.
 -0.02678571  0.13461538  0.13461538 -0.03526187 -0.03513099  0.
 -0.03517316 -0.03521826 -0.03521924  0.          -0.01978175 -0.01590909
 -0.01464286 -0.03528627 -0.03510685 -0.03528627 -0.5          0.04761905
 -0.23148148  0.          0.          -0.5        -0.05        -0.00535714
```

Results for GOT dataset:

- Initial opinion:

```
array([ 0.          ,  0.1875      ,  0.2          ,  0.5          ,  0.1875      ,
       0.5          ,  0.5          ,  0.1875      ,  0.          ,  0.          ,
       0.          ,  0.1875      ,  0.03116883,  0.06597403,  0.10416667,
       0.25         ,  0.56818182,  0.          ,  0.          ,  0.          ,
       0.          ,  0.          ,  0.          ,  0.          , -0.2         ,
      -0.05         ,  0.          ,  0.          ,  0.23333333,  0.          ,
       0.5          ,  0.          ,  0.23333333,  0.          ,  0.          ,
       0.5          ,  0.          ,  0.23333333, -0.23181818, -0.23181818,
```

- Change in opinions:

```
[ 1.87500000e-01  0.00000000e+00  5.00000000e-01  2.33333333e-01
   5.00000000e-01  1.87500000e-01  5.00000000e-01  0.00000000e+00
   6.82575758e-02  0.00000000e+00  5.00000000e-01  3.11688312e-02
   1.87500000e-01  1.04166667e-01  7.89935065e-02  1.04166667e-01
   0.00000000e+00  2.08131313e-01  0.00000000e+00  0.00000000e+00
   1.04166667e-01  1.04166667e-01  0.00000000e+00 -4.37500000e-02
  -5.00000000e-02  1.25000000e-02  0.00000000e+00  0.00000000e+00
   0.00000000e+00  3.66666667e-01  0.00000000e+00  2.33333333e-01
```

Bot Detection:

1. The data we have does not contain labels defining which account is bot and which is not. So we have used unsupervised learning model in this part to detect bots.
2. We are using K-Means to detect bots in the dataset.
3. We pass important features to K-Means and divide the screen_names into 2 clusters, either of which can be bot class.
4. Then we again apply filters to the data to determine the possible bots in the dataset.
5. The features that we pass to the model is as follows:

Table 2. Bot Classification Variables By Area of Analysis

| Area of Analysis | Variable |
|------------------|--|
| Profile | Absence of id |
| | Absence of a profile picture |
| | Absence of a screen name |
| | Has less than 30 followers |
| | Not geo-located |
| | Language not set to English |
| | Description contains a link |
| | Has sent less than 50 tweets |
| | 2:1 friends/followers ratio |
| | Has over 1,000 followers |
| | Has the default profile image |
| | Has never tweeted |
| | 50:1 friends/followers ratio |
| | 100:1 friends/followers ratio |
| | Absence of a description |
| Text Analysis | Levenshtein distance between user's tweets is less than 30 |

| | user_id | screen_name | lang | followers_count | friends_count | profile_url | description | location | ratio | cluster |
|-----|---------|-------------|------|-----------------|---------------|-------------|-------------|----------|-------|---------|
| 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0.0 | 1 |
| 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0.0 | 1 |
| 2 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0.0 | 1 |
| 3 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0.0 | 1 |
| 4 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0.0 | 0 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 195 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1.0 | 0 |
| 196 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0.0 | 1 |
| 197 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0.0 | 0 |
| 198 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 0.0 | 1 |
| 199 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0.0 | 0 |

Results for GOT dataset:

Possible Bots

1. Ksivananth
2. rushi_argula
3. Harshith_22
4. Sahulha24978411

```
if(df0['location'][i]==0):  
    #print("inside ratio")  
    if(df0['description'][i]==0):  
        #print("inside loc")  
        if(df0['followers_count'][i]==1):
```



Results for Kashmir dataset:

Possible bots:

1. Jenin65149160
2. usman30920808
3. IndianBoy092

```
if(df0['ratio'][i]==1):  
    #print("inside ratio")  
    if(df0['location'][i]==0):  
        #print("inside loc")  
        if(df0['followers_count'][i]==1):  
            if(df0['description'][i]==1):
```



Stance Analysis : GOT dataset

Procedure :

1. Pre process dataset.
2. Identify polarity and subjectivity of tweets
3. Cluster users based on their modularity and polarity.
4. For each cluster :
 - a. Identify polarity by max count
 - b. Identify subjectivity by max count
 - c. Calculate polarity
 - d. Calculate subjectivity

Plot the result.