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Prominent Actors Among The Bollywood Film Industry

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Abstract

The people are interacting with other people for their various needs and as a matter of social concern. They need to interact with the other people to construct a social network. The film industry has a lot of people like actor, actress, writer, director, musician to name a few. The industry has so many cast acted in so many movies over the period of time. They may sometimes long-lasting or they may not survive in the industry due to various reasons behind it. The problem of identifying the prominent person in the film industry is an interesting one. The Bollywood industry in India is one among the oldest one in the country and also it produced so many popular actors and actress in the last decades. This research is focused on identifying prominent persons, the actors and/or actresses, from the Indian Hindi Cinema industry. In support of finding the solution, a dataset with the movie details over a period is considered for the study. The measures of social network analysis are applied over the dataset and the results are discussed as part of the research.

Keywords: *Social Network Analysis, Degree Centrality, Betweenness Centrality, EigenVector Centrality, Prominent Actors, Bollywood Industry*

1 Introduction:

Identifying the most prominent actors in the network is a quite natural query in the social networking environment. This has wide variety of useful applications in the real-world scenario. Being prominence in real life situation will provide more advantages and at the same time some inconveniences also. The research question here is how to define or declare that the person is so called "prominent". The identification of the prominence node in the networked world would be an important study. The measures of Social Network Analysis (SNA) came into the picture to answer such a question. There two types of measures in SNA. They are (i) Centrality Measure and (ii) Prestige Measure. The centrality measure, as the name suggests, it defines how 'central' that a node or a person is. On the other hand, the prestige measure defines how many persons know the individual. For example, if a blog is posted in an Online Social Networking (OSN) site such as Twitter, then there may be a number of responses for the same, what is otherwise called as retweet. Thus, a person's tweet may become viral based on the number of retweet and hence he is called as prominent in the environment. The prominent people will have a large number of connections in their network. This is being identified by the degree of a node or set of nodes in the entire graph. In some of the literatures, the terms influential actors, authoritative actors, main actors are synonymously used. The following figure-1 illustrates the sample graph structure which consists of 16 vertices and two of the promising prominent vertices.

The cine actors can be represented as a structure of a graph. The vertices of the graph represent actors and the edges represent the acted in the movie. In such social network structure, the prominent actor identification is one among the major tasks. Therefore, the prominence in the social network is the most important vertex. Among the measures of social network analysis, the centrality measure is the mostly applicable one. The research problem identified in this paper is to identify the main actors involved in the cine actors' network. It is being achieved by applying the measures of social network analysis.

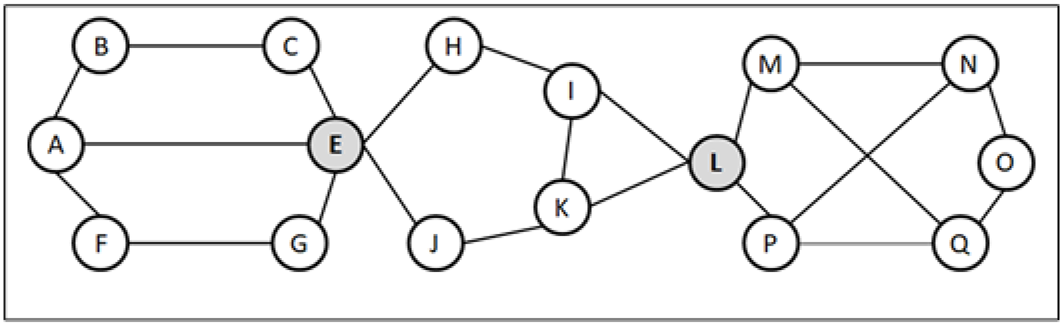

Figure 1. A sample graph with two prominent vertices (E and L)

The actor or group of actors are considered as prominent, if the measures have some threshold value. This is being calculated by the measures of social network analysis such as betweenness centrality, closeness centrality, degree centrality, eigenvector centrality and influence range closeness centrality. The threshold of these is fixed as a mean of the scores of all the centrality measures. It is compared with the mean score of all the centrality measures for the individual actor. If the value is either greater than or equal to the threshold, then the actor or actress represented by the vertex is having considered as "prominence" in the entire network. The reason for selecting the centrality as a measure to identify the prominent actor is this is used to concern about the "importance" of the vertex or the set of vertices of the graph.

The paper is further organised in the following manner. Section-2 describes the earlier research work which provides the support for this research. The dataset and the methodologies applied to find the solution to the problem taken through this research is explained in Section-3. The results obtained by the methodologies are elaborated in Section-4 and finally in section-5 the concluding remarks are given which summarises the problem identification and the results.

2 Related Research Work

This section describes the earlier research work carried out by the other researchers in the same domain. Social networks can be constructed on prominence actors of collaborations [1]. It creates clusters of objects on naturally sorted into teams. The prominence measures were applied over the knowledge sets and the algorithmic program outperforms with existing well-known algorithms. Further, it tends to provide an elaborated study of the sensitivity of the proposed algorithmic program to totally different knowledge sets and therefore the style decisions inside the algorithmic program that a user may need to alter.

Most analysis has targeted on the friendly relationship contradiction and its implications for information transmission on unweighted graphs. [2] studied the friendship paradox using egos and alerts. It need not be necessary that the best friend of a person can have more friends, in nature. This is being tested by the study. This phenomenon is also studied by the authors by using social network dataset and mobile dataset. It just explores a simple dynamic model.

Community discovery is an interesting and ever-green field of research in multiple domains. It is used to identify the targeted customers for marketing and other useful purpose and objectives. There are wide varieties of several approaches proposed by the researchers in the past. Finding a social role may have a great influence in the entire network structure [3]. The study investigates the member's activity, shared content and position within the network. It identified ten core roles. The identified roles participate in the community contribute to the creation in social practice.

A link analysis technique can be used to identify the authoritative users [4]. The common controversy with this approach is to justify which nodes of the network should be considered as authoritative. The other problem is that how many users should be chosen as authoritative. This proposed a new model based on Bayesian Information and Expectation Maximisation. This technique permits to mechanically discriminate between authoritative and non-authoritative users.

Online marketing campaigns and homeland security surveillance are some of the interesting applications in which the detection of node activities has strategic importance [5]. It explores the peer-to-peer exchanges of ideas over the network. The proposed models are well tested by using large social media datasets. This model also tested the social media communities of different sizes.

The actor model is one among the oldest models for message passing concurrency model [6]. The objective of this model is to provide the languages and libraries which influenced the design and rationale. Though the model is 43 years old, it still considered as the prominent model for message passing mechanism in a networked environment. This is the base model mostly used by both the academia and industry. The contribution includes the nomenclature, substrate and categorisation.

Poetry and drama are the most influential factors which will increase the literature to the citizen of any country. One among the oldest poetry is the Tang Dynasty [7]. The poet relationships and the sub-communities from the social structure were identified from the poetry. It also used the social network analysis techniques and visualisation to represent the community structures identified from the study. It would be useful to the humanities students with similar interests.

The node identification and the role of the node in the social network is an interesting phenomenon [8]. A single indicator is insufficient to evaluate the role of such node and hence there is a requirement to introduce multiple indicators for such evaluation to act as a bridge in the network. A weak correlation can be used to efficiently assess the different characteristics of a single node. The difference between the indicator’s relationship and the statistical correlation is used to determine the candidature of a node.

Dynamic networks are changing its structures over evolution. The nodes and edges of such networks changes by adding, removing, updating during the period of time. There is a need for an incremental algorithm which detects the changes that happens in such networks by using all pairs shortest paths [9]. The devising of such algorithms will provide the benefit of early pruning. It will update the changes so dynamically as and when there is some change in the network.

Generating more information traffic and increasing the information exposure are the two key issues in social media [10]. The connected users are considered as more influential users. This is being conducted by analysing tweets and applying the social theories. It is also observed that the connected user’s position affects the influence of a user. The study revealed that the high-status of connecting users contributes more on information diffusion. This will enhance the users to provide content-based service on user profile and location.

There are different ways suggested to find the leaders in the literature in the past. One suggests applying the social network measures and the other suggests having multiple methods [11]. One such was to find the number of connections in the leader’s network. A person who has more number of connections would be considered as a leader. The hybrid technique is applied over the higher education to identify the leader. It also assessed whether the suggested methods find the same leader or different. The results obtained by these two methods either the same or different.

Location-based recommender systems are attracting the researchers in the recent past. This can be provided by the online social networks based on the analysis of the users' attributes. The geo-location based online social networking is the recent research in which the users' interaction behavior can be used for further marketing activities [12]. It is also determined whether or not the user's mobility pattern can be used to predict user's interaction behavior apart from the usage of friends' interactions and network tie formation. It is also found that the distance between users to form a network tie is not a factor of concern.

Opinion mining is an interesting research domain. It gathers opinion from various sources. With the advent of online social networking sites, it is now become possible to collect such information from the sites such as twitter and Facebook [13]. A new measure is used to evaluate the opinions shared by the users among the twitter users as tweets. A model is also proposed to find the influence of the user based on the attractiveness compared to the other actors in the network. The informed decision-making process can be used by different fields like education, marketing and politics.

Terrorist network can also be presented as a social structure. A group of terrorist will also assist the other group for other activities like training. In such cases, it is also vital to analyse the terrorist network by means of identifying the prominent actors [14]. Some of the machine learning techniques is used to compare the results obtained with the social networking technique such as k-core optimization and centrality measures.

There are different ways to find the prominent actors in the network environment. One such way is when a person is continuously interacting in the group then he or she may be considered as a prominent actor [15]. The participation of the member in the group is assessed by associating with a specific time.

Social network can be formed by having mutual relationship or a common interest. It is understood that there is no limitation or criteria to find a friend and accepting friend request in such environment. A person with some kind of disorders like Obesity can be a part of concern to form the network [16]. The dissimilarity of friendship is also a major factor to form the network. It is a great idea of this kind to be familiar and to analyse the dynamics and influence based on homophily. It also try to identify the patterns of similar adults with the same criteria or factor.

The researchers, scientist and theorists are using a wide variety of theories over the past in support of their finding through the research. It can be used as a base that is required to defend for wide acceptance. There are two widely-adopted theories applicable in social network [17]. When a theory attempts to avoid explaining social changes through a specific chain of causality and reduce the scope of soeial and material elements the other one cuts the social theory boundaries.

Social network sites, like Facebook, Twitter, Renren and Sina Weibo, square measure currently changing into more and more widespread on the net [18]. For the past few years, varied analysis are created to research the topological structure and user behaviours of on-line social networks, that is sort of necessary for the understanding of human social behaviours, the development of current web site systems and therefore the style of on-line social networks new applications.

Promotional activities are highly essential as a marketing strategy for any product or service. This is vital part of the organization to attract the customers towards their product and/or services. The social network in today's scenario offers such a platform for promotional offers and activities through microblogging [19]. It is applicable for entertainment world including movies, dramas and television series. The measure and verification process are required on assessment aspect. The testing can also be done to evaluate the effect of such measure and verification.

The designers are playing a crucial role for any application in order to provide the effectiveness of the product and services. The social links are visible to the end-users through which they can access the required and necessary content. A framework offers a commonality of portability in which any product can be ported into it [20]. The social service platform also provides such a portability in which the blogging or posting of information by any user nevertheless of considering the geographical location is made possible. Social networking platforms also offer trust in terms of its properties. Sometimes, it is also possible that such availability of a framework can be misused in different applications.

A person is considered as influential, if he or she has most central part of his or her network. The individual will use the digital platforms for interactions. In case of the people who are living in remote areas such as villages, the platform and interaction would be crucial [21]. The network in which no one can trace the authenticity of the person along with its footage and trust is called as unknown network. It is very cumbersome to find the most influential persons from such a unknown network. A paradoxical methodology would provide the support and this is being made possible by a simulation study.

3 Materials and Method

This section describes the dataset used for the study and the social network analysis measures applied to find the prominent actors from the dataset.

3.1 Material

A Bollywood movie dataset is downloaded from the Kaggle website [22]. It contains the details of 1,284 movies which are released from 2001 to 2014. The number of movies released during this period is: 62, 79, 95, 88, 106, 60, 66, 98, 91, 116, 112, 99, 102, and 110 in the corresponding year. This research requires identifying the prominent actors than the details of the movies. Hence, the cast details from the dataset are partitioned into actor and actress who acted in the movie. It is removed the other details of the movie like Director, Genre and Writers. It is also found that four of such entries either in the actor side or in the actress side are missing. Such rows are removed to produce the dataset size of 1,280. It is considered as a preprocess step which is essential, as the actress name is not found in the dataset. It has repeated values of the same actors and actress names. Furthermore, it is summarized based on the actor and actor names. These yield 956 unique names of actor and actress. This is the dataset size considered for further study. The naming convention “node” is used to represent both the actor and actress. A graph has a common structure G = (v, u) where v is the number of vertices and u is the number of edges. A graph represents the connectivity between the actor and the actress who acted in the movies. The actor / actress represent the vertex and the acted with represents the edge. It is a 1-mode directed graph. The network is directed and unweighted graph. The names of the actors and actresses are identified by the vertex number itself, in order to preserve the privacy of the individuals, if any. The following figure-2 shows the visualization of the dataset.

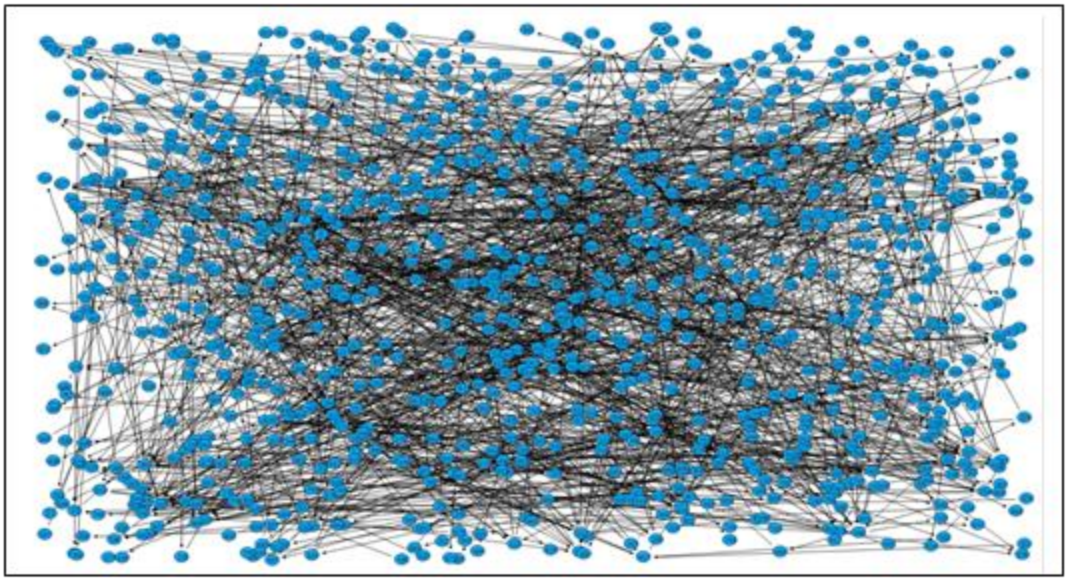

Figure 2. Who is connected with whom among the stars

3.2 Methods

In order to find the prominent actors, the centrality measures and prestige measures of social network analysis are applied over the final dataset which has 956 unique names. There are five different centrality measures used in this study. They are (i) Betweenness centrality (ii) Closeness centrality (iii) Degree centrality (iv) Eigenvector centrality and (v) Influence Range Closeness centrality.

The betweenness centrality (BC) identifies the influence of a vertex over the network. It identifies whether a vertex is reachable from a vertex i to another vertex j through the shortest path between i and j. The BC index of a node u is the sum of δ(s,t,u) for all s,t ∈ V where δ(s,t,u) is the ratio of all geodesics between s and t which run through u. It shows the nodes which are 'bridges' between vertices in the graph. The BC can be computed as:

$$C_B(v) = \sum_{s \neq v \neq t \neq V} \frac{\sigma_{st}(v)}{\sigma_{st}} \qquad (1)$$

The Closeness centrality (CC) scores each node based on their 'closeness' to all other nodes in the network. It shows the individuals who are best placed to influence the entire network most quickly. The CC index is the inverted sum of geodesic distances from each node u to all other nodes. It considers outbound arcs only and isolate nodes are dropped by default. It is measured as:

$$CC(v_i) = \frac{N-1}{\sum_j d(i,j)} \qquad (2)$$

The degree centrality (DC) measures the number of neighbors that a node has. It is determined by the number of nodes adjacent to a node. The index is the sum of outbound arcs from node u to all adjacent nodes. It scores the number of outgoing edges from a vertex. That is, it will tell us an actor acted with how many number of other actress. It is also called as "outDegree Centrality". It is measured as:

$$C_D(v_i) = \sum_{j=1}^{n} x_{ij} \tag{3}$$

The Eigenvector Centrality (EC) measures a node's influence based on the number of links it has to other nodes in the network. It then goes a step further by also taking into account how well connected a node is, and how many links their connections have, and so on through the network. It is a good 'all-round' SNA score and it helps to understand human social networks. This measure can be computed by the following:

$$x_i = \frac{1}{\lambda} \sum_{j=1}^{n} A_{ij} x_j \tag{4}$$

The Influence Range Closeness Centrality (IRCC) index of a node u is the ratio of the fraction of nodes reachable by node u to the average distance of these nodes from u. This measure is similar to Closeness Centrality but it counts only outbound distances from each actor to other reachable actors. This is the ratio of the fraction of nodes reachable by u to the average distance of these nodes from u. This is measured as:

$$IRCC = \frac{\frac{|J|}{(n-1)}}{\frac{\sum d(u,j)}{|J|}} \tag{5}$$

These measures are calculated using Social Network Visualisation (SocNetV) tool [23]. The scores of the individual measures are in different range. Hence, it is normalized by using the following formula in 100 point scale.

$$v' = \frac{v - min_c}{max_c - min_c}(new\_max_c - new\_min_c) + new\_min_c \tag{6}$$

The table-1 below shows all the actual centrality scores and the normalized centrality scores.

Table 1. Centrality scores before and after normalization (Partial list of Nodes)

Node	Centrality measures score					Normalized Score				
	BC	CC	DC	EC	IRCC	BC	CC	DC	EC	IRCC
1	0.00	1.00	1.00	0.00	0.00	1.00	100.00	4.00	1.00	2.00
2	391.00	0.00	9.00	0.16	0.10	6.00	1.00	32.00	34.00	76.00
3	0.00	1.00	1.00	0.00	0.00	1.00	100.00	4.00	1.00	2.00
4	978.27	0.00	1.00	0.01	0.09	12.00	1.00	4.00	4.00	64.00
5	147.64	0.04	1.00	0.00	0.00	3.00	5.00	4.00	1.00	3.00
6	2.00	1.00	1.00	0.00	0.00	1.00	100.00	4.00	1.00	2.00
7	2356.54	0.00	7.00	0.00	0.08	29.00	1.00	25.00	2.00	58.00
8	0.00	1.00	1.00	0.00	0.00	1.00	100.00	4.00	1.00	2.00
9	4179.77	0.00	11.00	0.08	0.10	50.00	1.00	39.00	17.00	77.00
10	0.00	0.33	1.00	0.00	0.00	1.00	34.00	4.00	1.00	2.00
11	145.00	1.00	1.00	0.00	0.00	3.00	100.00	4.00	1.00	2.00
12	144.00	1.00	1.00	0.00	0.00	3.00	100.00	4.00	1.00	2.00
13	0.00	1.00	1.00	0.00	0.00	1.00	100.00	4.00	1.00	2.00

14	0.00	1.00	1.00	0.00	0.00	1.00	100.00	4.00	1.00	2.00
15	0.00	0.50	2.00	0.00	0.00	1.00	51.00	8.00	1.00	3.00
16	143.00	1.00	1.00	0.00	0.00	3.00	100.00	4.00	1.00	2.00
17	1440.39	0.00	9.00	0.00	0.08	18.00	1.00	32.00	2.00	63.00
18	0.00	1.00	1.00	0.00	0.00	1.00	100.00	4.00	1.00	2.00
19	432.23	0.00	2.00	0.02	0.09	6.00	1.00	8.00	4.00	63.00
20	4880.20	0.00	28.00	0.21	0.13	58.00	1.00	97.00	45.00	96.00

4 Results

The dataset downloaded from the kaggle website is used to compute the different centrality measures and prestige measures. The non-zero scores of all the centrality measures correspond to the actors only considered for further study. The following figures represent the scores of centrality measures by means of histogram and the overall bar chart.

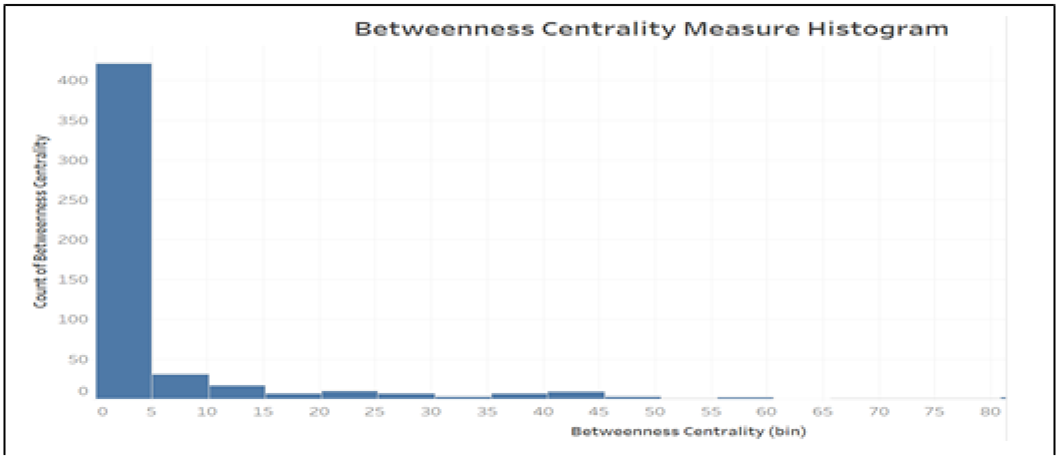

Figure 3. Histogram of Betweenness centrality measure

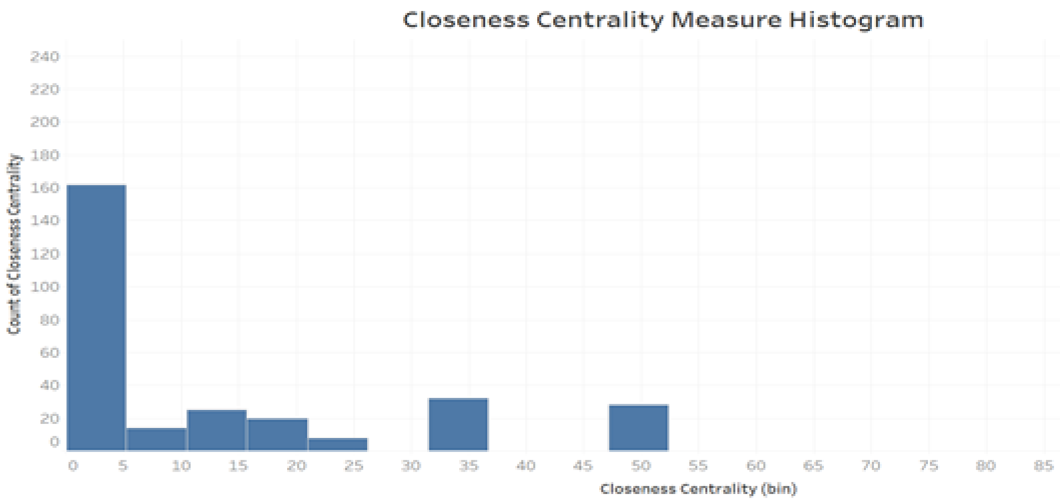

Figure 4. Histogram of Closeness centrality measure

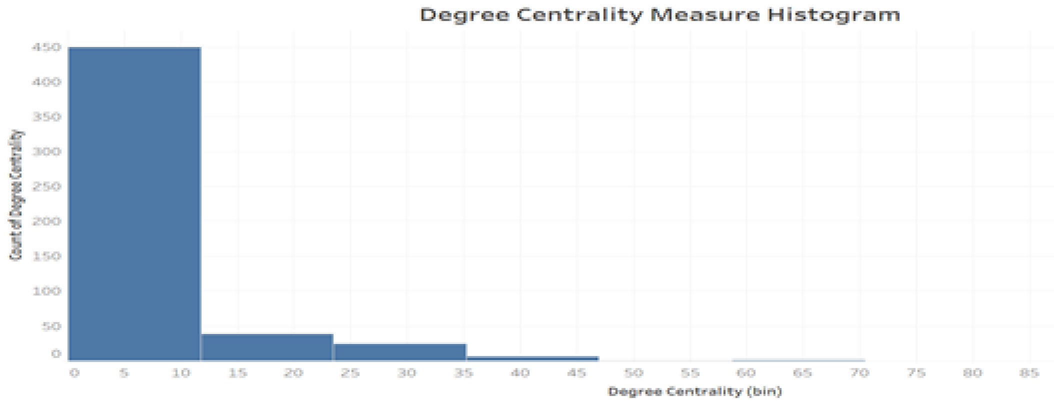

Figure 5. Histogram of Degree centrality measure

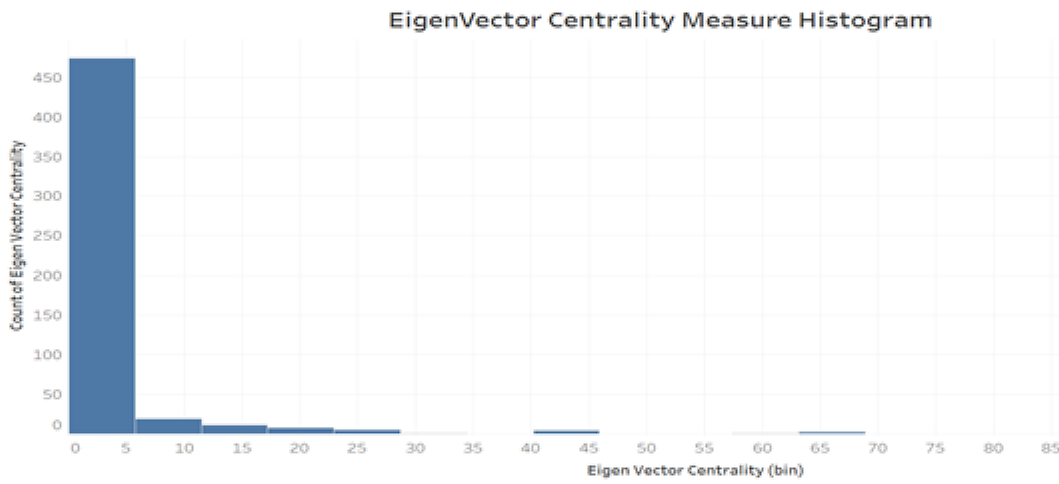

Figure 6. Histogram of Eigenvector centrality measure

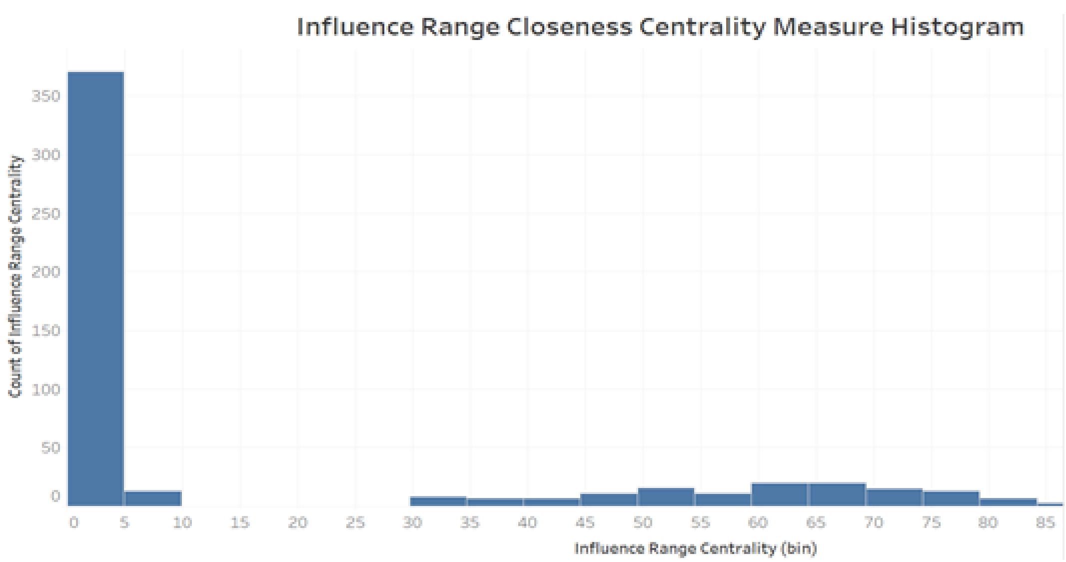

Figure 7. Histogram of Influence Range centrality measure

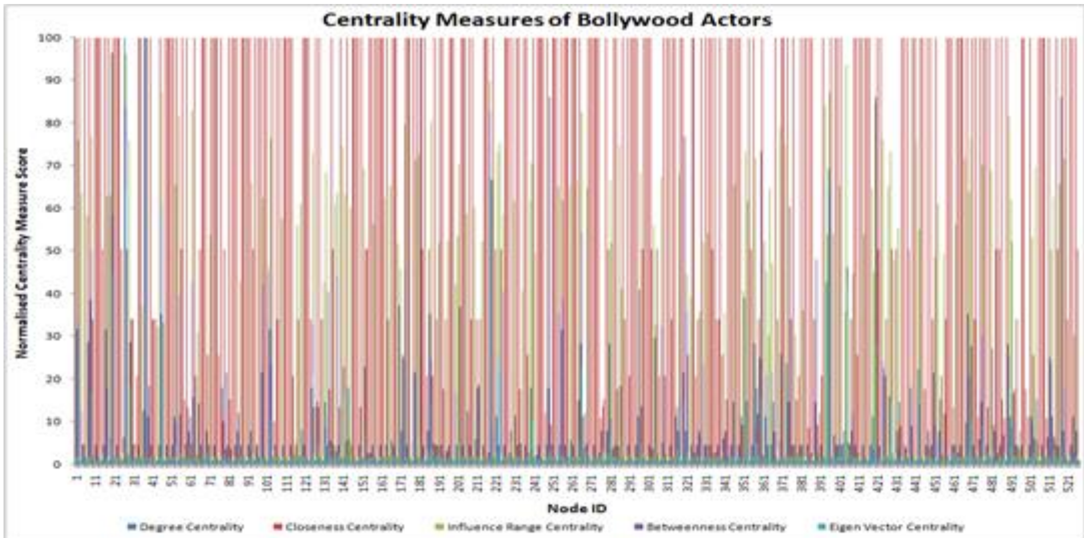

Figure 8. Normalized Centrality Measure scores of the Bollywood actors

The mean value of the individual centrality measures is calculated to find the mean value of all the centrality measures. It is calculated as 18. The mean values of the nodes are also calculated. The prominent actors are considered as one who have scored the mean value greater than or equal to 18. In this manner the following vertices scored the criteria: 1, 2, 3, 6, 7, 8, 9, 11, 12, 13, 14, 16, 17, 18, 20, 21, 22, 23, 24, 27, 29, 34, 35, 37, 38, 40, 45, 46, 48, 49, 50, 51, 52, 53, 54, 55, 57, 59, 62, 63, 67, 68, 69, 72, 73, 74, 75, 77, 81, 83, 84, 85, 88, 89, 90, 91, 92, 95, 97, 98, 99, 100, 101, 102, 103, 104, 106, 108, 110, 111, 112, 113, 114 , 120, 121, 122, 123, 125, 127, 129, 132, 135, 138, 140, 141, 143, 146, 147, 148, 149, 151, 152, 155,156, 158, 159, 160, 161, 162, 164, 167, 168, 169, 170, 173, 174, 175, 176, 178, 179, 180, 181, 182, 184, 187, 189, 192, 193, 197, 198, 199, 202, 203, 204, 205, 207, 209, 215, 216, 217, 218, 220, 222, 223, 226,227, 228, 230, 231, 232, 233, 236, 237, 240, 241, 243, 244, 245, 246, 248, 249, 251, 252, 253, 254, 255, 256, 257, 258, 259, 261, 262, 263, 264, 265, 266, 270, 271, 272, 273, 274, 275, 279, 281, 283, 284, 286, 288, 290, 292, 293, 294, 295, 296, 297, 299, 300, 301, 302, 304, 308, 309, 311, 312, 314, 315, 317, 318, 319, 320, 321, 324, 325, 329, 330, 331, 333, 334, 336, 339, 343, 344, 345, 347, 348, 349, 352, 354, 356, 357, 360, 361, 366, 368, 370, 371, 372, 373, 374, 375, 377, 381, 383, 384, 386, 387, 389, 393, 394, 396, 397, 399, 400, 402, 405, 409, 410, 412, 413, 415, 416, 417, 420, 421, 423, 424, 427, 428, 434, 435, 437, 440, 441, 442, 444, 445, 447, 449, 452, 458, 459, 460, 463, 464, 465, 466, 468, 469, 470, 471, 473, 475, 476, 477, 478, 480, 481, 484, 486, 489, 490, 497, 498, 501, 504, 506, 507, 508, 509, 511, 512, 515, 517, 518, 519, 520, 522, 523 and 525. There are 63 prominent actors identified from the network out of 527 vertices. It is just 12% over the number of actors acted in various movies during the period mentioned in the dataset.

5 Conclusion

Social Network connects the individuals and organization. The network structure contains the set of actors and ties and the same can be represented as a graph. The film industry has wide variety of people. In particular, the actor and actresses are given more importance for the success of a movie. It is also noted that not all the actors and actresses who acted in wide variety of movies getting popular in the cine industry. Only few of them are able to survive in the industry and the others are not. The actors and actresses who are in the industry get popular and they are called as prominent persons. This research is focused on identifying the prominent actors and actresses from the Bollywood industry. A dataset contains 1,284 movies released for a period of about fifteen years is studied to find such persons. In order to find the same, five different social network analysis measures are applied over the dataset. The centrality measure captures the prominence of nodes in the network. The results shown that 12% of the actors acted in the period are the prominent persons. The vertices are the actors and the edges are the ties.

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