Based on Competitive Marketing: A New Framework mechanism in Social Media

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Abstract. In social merchandise, there are many similar products emanating from many enterprises. The enterprises want to scatter details for their products so that they are known widely in social media. This is because they believe in competitive advantage for commercial products. There has been research merging two enterprises for worldwide circulation and popularity. The initial procedure entails finding seed points then later disseminate details separately as per the separate Cascade approach. The aim is finding an initial common ground the dissemination to social platforms. Significant is also how fast data diffusion can be done. Data effect will arise from either none, one or more nodes in a social interconnection. Evaluation is also accomplished on the number of fraction parts in various sections are affected by the different rates of data diffusion. The simulation result for proposed framework introduces good outcomes result.

A- Keywords: Social Media, Competitive marketing, Cascade Approach, Degree Centrality, Eigenvector centrality.

1. Introduction

To be able to sell competitively, it requires many competent producers to satisfy clients’ requirements. Most competitive markets hang on variety of clients and producers’ two enterprises want to perform better, they need their data say data 1 for enterprise E1 and data 2 for enterprise E2 to be enlarged. This would enlarge client reach. Dissemination of details requires transmission through networks [1]. The result changes in selection characters, diffusion promotion in relation to a commodity prior to its induction or raise seller status [30]. Today, several companies diffuse their information concurrently [2]. Social platforms open a comprehension on dissemination of product details worldwide [3,4]. Earlier, there was a limitation of dissemination methods like face to face, print media, Facebook. Disseminating details applies to other arenas like physics, biology among many [21, 32]]. Concentration is mostly on a certain transmission, pathway, intelligent linkages which have an effect in dissemination. There is examination on reasons for mouth dissemination and viral merchandise to understand transmission details [5].

This is inclusive of advancement of diverse processes in game theory framework. The authors in [7] have introduced a basic flowchart problem regarding integration of merchandise processes. Engaging discussion on mouth dissemination also needs attention to be given to dissemination via social platforms by many firms, enterprises and political groups to enhance product knowledge simultaneously [29]. For instance, while enhancing the newest Galaxy mobile device by Samsung could also mean concurrently announce the newest
iPhone. Several models for competitive dissemination exist [6]. Initially, an assumption is made that one of the candidates has hitherto selected their procedures and evaluate the algorithmic issues for establishing the most preferred outcome [4].

The aim is outmost effect [2] or lesser niche impact [8]. Also, an enterprise could get the niche as an alternative method [9]. Facebook examination dissemination impact was undertaken using degree centralization (local node element) and rank degree process (chosen method for linkage) from seed selection. The techniques provide selection of various seed areas of significance in the interconnection. Two companies were taken into consideration in the suggested framework with two engaging data concurrently. Both companies have a fixed starting budget to be used for choosing seed areas. The companies will select their seed areas concurrently and further, information will be spread as per ICM [10]. ICM uses straight graphs and a junction for transmission within the parties. Within the interconnections, areas receiving data are within the same association. For considerations as informed, the impact of the information ought to be higher or same as the entry value. Once a point has received communication, it can pass information to an adjacent point. The process is ongoing, and it implies that a point transforms from non-informed to informed where the reverse is false. In cases where a point receives information from more than one other points, the high impact data is selected from a point [27]. For equal impact, a point is considered to offer support for just one data with equal chance [28]. The suggested model can locate the significant spreader in social interconnections for both companies.

The rest of the research is arranged in parts as section 2, which is comprehensively discussing similar studies of the suggested framework, section 3 explains the suggested framework, selecting spreader point and data diffusion by employing separate Cascade approach, while in section 4, the simulation and results were presented. Section 5 concludes the research.

2. Related work

Many research studies exist on competitive data diffusion [11,12,17]. Easy apprehension of competitive data spreading is through game-theoretic models. Application areas entail the mathematics science, software engineering, microbiology, health science, management and public economics [13]. In other study, the cascade dynamics of multiplex propagation research was undertaken [14], to exhibit the random connections between far nodes highly impact the spread of disease or data given the contamination can be conveyed by a sole agile node. Nevertheless, when the dissemination necessitates concurrent exhibition to a variety of sources of actuation, known as countless dissemination, the impact of random connections makes dissemination attainment harder. Reference [16], evaluated the effects of various artifacts and terrestrial relationships on diffusion in composite disclosure interconnections. The outcomes were, one, the community system and its connections with interrelate weights, and two the heterogeneous and explosion task designs on the associations, are significant in spreading speed.

Reference [15], discussed a impact of diverse temporal and topological correlations based on circulation in different platforms over the internet. This paper has shown two important points: (a) the community framework and its correlation with connect weights, (b) The bursty and inhomogeneous activity style in firms, which has a substantial role in spreading speed.

HE et al. [18], The suggested mechanism is used to combine different approaches and compare the content of social media for business competitors. The seed selection techniques and ICM helps highlight the perception of trading and methods on how fewer beginning points can impact the whole interconnection. The changes of this dispersal can be comprehended by ICM.

The investigated the global cascades in random networks have been used in reference [22], authors presented the global cascades in social and economic work, as well as cascading defeat at networks occur rarely. So, the global cascades and cascading defeat are large when they occur. They studied binary-decision work in various case. When the network of interpersonal influence is sufficiently sparse, the propagation of cascades is limited.
by the global connectivity of the network; and when it is sufficiently dense, cascade propagation is limited by the stability of the individual nodes.

Authors in [23] have introduced threshold models for collective conduct via behavioral threshold. The analysis work on binary decision of actor/points in a network. First with a frequency allocation of thresholds, the work allow calculation of the ultimate or “equilibrium” No. making each decision. The stabilization of equilibrium outcomes against differences possible alterations in threshold allocation is also considered.

M. Karsai et al. [24], presented the impact of various topological and temporal engagements on pervasion in complex communication networks. In additional, paper showed that (i) the community temple and its engagement with link weights and (ii) the inhomogeneous and bursty vigor patterns on the links, plays an important role in spreading speed.

The seed selection techniques and ICM helps highlight the perception of trading and methods on how fewer beginning points can impact the whole interconnection. The changes of this dispersal can be comprehended by ICM.

### 3. Proposed Framework

Assume $F(X, Y)$ be an unweighed and undirected link, $m$ points, $X = \{1, 2, 3, 4, \ldots, m\}$, and ordering of links $Y$. So, we assigned close to $i \in X$ as $N_i(F) := \{ j \mid (j, i) \in Y \}$, the extent of $i$ as $d_i := |N_i(F)|$. A threshold (quantity of information to a node) for point $i$, designated as $\theta_i$ is a chance linking $[0, 1]$. The area within higher data impact or the same as the threshold is selected as impacted by that data. The impact of data is explained as the impact on the behavior of point as a result of the data. Its value is about 0 to 1, with, 0 implying no impact and 1 implying total impact of data.

There are two organizations, $f_1$ and $f_2$ and two data 1 and 2, separately. In an interconnection, a point receives information from not less than one data, supporter entails point is aiding one of the data, and non-spreader/unknowledgeable implies lack of information to the point or received data has less influence in comparison to the entry of the point. Points at social interconnection each reinforce data 1, data 2 or persist as a non spreader.

The suggested structure brings out six sections for every point, $S, A, B, AB, a$ and $b$ as shown in figure 1; where every variable is purposed variables and the total of all the sections is always 1. $S$ signifies a section for the unknowable end, $A$ and $B$ signify sections for knowledgeable ends by data 1 and data 2, separately and $AB$ signifies sections for ends enlightened by both data 1 and 2, separately. Let $\alpha_1$ and $\alpha_2$ be the impact of data 1 and 2, separately ($0 \leq \alpha_1 \leq 1; 0 \leq \alpha_2 \leq 1$). The results of $\alpha_1$ and $\alpha_2$ are most likely distinct for separate ends in the internetwork. Various colors are employed for deeper comprehension, green for data 1 and yellow for data 2. For instance, an end in section $AB$ receives information from data 1 with value $\alpha_1$ exhibited in red; likewise, the impact of data 2 with value $\alpha_2$ exhibited in yellow. A point in section $a$ is advocator of data 1. Thus, it is exhibited fully in green color. Likewise, for a point in section $b$ which advocates for data 2 and exhibited in yellow color only, (Note: For a point, if $\alpha_1 = \alpha_2$ then, it advocates for both data with a likelihood of 0.5). $\alpha_1$ and $\alpha_2$ signify the rate of diffusion of data 1 and data 2.
Let, $\alpha_i^{par}$ become the impact of data $i$, ($S$, $i = 1, 2$) on the origin point, $\alpha_i^{ch}$ become the impact for data $i$ at child point, $d_{ch}$ be a degree for child-point, $k$ become a group of children part, $A$ become the nearest array while $\alpha_i^{sib}$ become a impact for data $i$ at point sib of parent point, when $sib \in k$. So, the impact for data $i$ at point $ch$ is revealed in equation 1.

$$
\alpha_i^{ch} = \sum_{par \in k} \left( \frac{\alpha_i^{par}}{d_{ch}} A(ch, par) \right) + \sum_{sib \in k} \left( \frac{\alpha_i^{sib}}{d_{ch}} A(ch, sib) \right)
$$

(1)

Where $ch, par, sib \in V$. At first, all ends apart from seed ends are in the uninformed section. Companies select seed end concurrently from their data. A company can employ a seed end as a seed on condition it has forecasted for that point. The suggested model is explained in the five subparts with time complexity of $O(XY)$.

1-At the network compute the cost of each point.
2-Set every enterprise capital (Firm).
3-Choose initial station(s) for every enterprise (firm).
4-Disseminate details with cascade technique and select defender (s) for every detail.
5-Replicate strides 2, 3, 4, 5 at different instances.

3.1 Cost computation pertaining every station (point).

The station (point) cost details the price of a station to selection of seed points. The price of estimation accrues the enterprise. The value estimation is computed by central tendency and it designates chance doe transmission [16]. Trusted calculations for central tendency entail calculation average, the median, and the point. Any data exhibits two types of outliers: Bad outlier, and Good outlier. Any inspection falling on an abnormal interval from other figures in a relevant representative from a populace is a bad outlier, and hence median is employed. Consideration is on the level of an end for calculation of the cost. Median is chosen in this case as there are bad outliers. Unit cost is allocated to the ends with central tendency and then the cost of the rest of the ends will be based on linear techniques. Algorithm 1 displays the end cost approximation. Time difficulty for establishing the central tendency value by employing median takes equation 2, with $n$ existence the sum of number of points in the interconnection.
Establishing Time \( \Rightarrow O(n) \) \hspace{1cm} (2)

| Algorithm 1: The price estimate of a station (point) |
|--------------------------------------------------|
| 1- Computing the central inclination degree via median. |
| 2- Allocate every station (point) with degree like central inclination degree as unit cost. |
| 3- Compute every station (point) price via linear method |

Let \( F(X, Y) \) designate an undirected link in \( V \) stations and \( E \) edges. The degree of every station \( i \) is \( d_i \) and the degree of central tendency part is \( dct \). The price of every station \( i \) is \( c_i \) Then, the linear technique for price computation is (3):

\[
\forall i \quad c_i \frac{d_i}{dct}, \text{ where } i = 1, 2, 3, ... \ldots x
\] \hspace{1cm} (3)

3.2 Budget initializing for an enterprise (firm)

Each enterprise, \( Fi \), has a starting estimate \( Bi \) (Bi=1) assigned for seed choosing. Each enterprise initially chooses the end with the degree of central estimation as a seed and must be good for the seed end, any competitor will be a winner or loser from the other enterprise. Any changes happen at the onset. The inference is if the f-No. of enterprises, then, the challenge in time for initiating the forecast is \( O(f) \), with, \( f \llll n \).

3.3 Selecting Spreader Point

There are several ways to estimate a station (point) impact. The following methods concur with seed choosing:

B- Degree Centrality

This technique chooses significant stations (points). With several connections there is more impact on a station. To compare effect stations in different links, the normalized level centrality is illustrated:

\[
Dc(i) = \frac{d_i}{n-1}
\] \hspace{1cm} (4)

With \( n = |X| \) shows stations (points) in G and \( n-1 \) is the greatest attainable level [22,23]. So, for heavy neighbouring matrix components of the graph, estimating the middle level joining the graph takes \( \mathcal{O}(X^2) \). At sparse array constitution of the graph, it takes \( \mathcal{O}(Y) \) to establish the value of the level of centrality for all stations (points).

C- Rank Degree

This method is constituted from the notion of the challenge in picking a lesser subgraph containing elements of topology regarding the initial graph. An impact station is established by a sampling method with criteria that i. (a) the fraction of top-k regular ends in a demonstrations and within a graph is averagely greater and (b) the
categorization of these ends in the demonstrations take place near to the real categorization within a graph [14]. The time challenge of ranking degree process is $O(n^2)$ for scanty array.

**Algorithm 2. Rank level**

1. Adjust values: a- number of initial seeds,
b- f , c- base model size x
2. **INPUT:** Undirected a graph; F(x,y).
3. Allocating :(Seed) $\subseteq$ s random points chosen consistently.
4. Sample $\subseteq \emptyset$
5. Until simple size $<$ target x
   Do
   (New seed) $\subseteq \emptyset$
   for $\forall i \in (seeds)$
   Do
   Rank $w'$ friends regarding their level estimates
   Rule chosen:
   a- RD max $\in$ chose a max degree (top -1) a friends of $w$
   b- RD (f) $\in$ chose a top – k friends of $w$, so; $k = f$, $0 < f \leq 1$
6. Improve the current base within a chosen edges; (w. friend (w) on the top – k)
   within a symmetrical.
7. Add to (new seeds) the top-k friend of w
   End for
8. Improve graph G: eliminate form the graph all present chosen edges.
9. (Seeds) $\subseteq$ (new seeds)
10. If (new seeds) = $\emptyset$
    Repeat step 5
    End if
11. End Until loop

**D- Eigenvector centrality**

Presume the eigenvector centrality which the effect for stations is not set using its intermediates, but also established using every intermediate effect [3]. The centrality of a points corresponds to the total number of centralities of stations linked. Station significance i, is shown via $X_i$:

$$X_i = c \sum_{j=1}^{n} a_{ij} x_j \quad (5)$$

That can write in the matrix below:

$$X = cA \xrightarrow{x} \quad (6)$$

So, c is a proportion constant. Time complication for EC is $O(V^3)$.
3.4 Data Spreading

Stations (points) selected to be starter spreaders are allocated values of $\alpha_1$ and $\alpha_2$ as 1. After the selection of the seed point(s), independent cascade is employed for viewing the number of ends informed by every data. The distribution procedure entails three basic components: transmitter, Receiver; and Medium.

3.4.1 Cascade Model

Cascade dissemination entails immediate trees where seed stations are origin points. This results in details effect on stations. Siblings have an effect and stations sharing parents are considered on border lines between siblings in the initial establishment, the outcome is the impact of every data on points part by part. The influence of siblings and points with similar parents at every part is also regarded if there is a border between siblings in the actual interconnection. During dissemination the design and time factor are of significance. If details are taken as initial transmitters or non-transmitters, the technique is simplified. The easiest method to explain the diffusion technique is in consideration of a data to be either spreader (i.e., is in possession of the data with dissemination attempts) or non-spread. The depiction is in Figure 2-A illustrating the ICM dependent dissemination. Station (point) 2 is the seed station for the first details and station 5 the seed station for the second details.

The illustration in form of a tree is due to concurrent transmission. Seed endpoints are initial stations for the information. Figure 2-B depicts demonstration for the connection with station 2 as seed station for the first details. Information is disseminated simultaneously after seed station choice is done. Details are disseminated part by part like a tree with station 5 being the seed station for the second details as depicted in figure 2-D.

Circulation of details (Data) is after stations seeds are chosen. Data will be diffused section by section as per the tree-like figure in relation to seed point in the data. The sibling's connection is depicted by 2-way colored arrows. Circulation of details to siblings affects both siblings. The fig.2 - b illustrates the tree same anatomy for seed (point 2) of a data 1 and this data won't disseminate beyond seed (point 5) of the data 2; so, elimination is done for seed 2 data and un reachable points to point 2. The outcome tree is exhibited in fig. 2- c. next, evaluation of the influence of data 1 disseminated by seed (point 2) on each point of the interconnections is done. Likewise, the influence of data 2 prevalence via seed (point 5) on each point of a similar interconnection is exhibited in fig. 2- d and -e. Lastly, the fig. 2-c and e, it is easy to examine the impact of data 1 and data 2 on the sample interconnection as exhibited in fig. 3-a.
In an aggressive domain with two companies F1 and F2, three cases can arise, one, company F1 wins, two, company F2 wins, and three a tie. So, we can see in Fig. 3-a, point 2 is a seed for data 1 and point 5 is a seed for data 2. The influence of data 1 on points (1, 2, 3, 4,.., 10) are greater in comparison to data 2; thus, support for data 1. Likewise, the impact of data 2 on points 5, 6, 7, 8 and 9 is greater than data 1; thus, reinforcement for data 2. This is a tie case because of the same supporter number for each.

The procedure can moreover be expanded to several participants or organizations. Figure 3-B illustrates a company F1 winning. Point (3) is a seed and the points (1, 2, 3, 4,.., 10) are supporters for data 1. Point 5 is the seed and points (5) and (6) are supporters for data 2. Here, the points (7, 8 , 9) are similarly impacted by both data; thus, support for each data with same
The decision is arrived at after comparison is made on the values of the impact of data at every end. The time difficulty for disseminating data is $O(XY)$.

## 4 Simulation

The Facebook dataset was considered for setting statistics as exhibited in Table 1. It entails ‘circles’ (or ‘Friends lists’) and it is an easy (undirected and unweighted); graph with people being points and their friendship being at the border. By employing the datasets specified, simulation is affected by the suggested framework detailed in section 3. The post data dissemination is evaluating the number of fraction pints impacted by the data with the number of informed fractions supporting the data. There is possibility of points evenly impacted by both data under the same probability. During the simulation using MATLAB 10 program on Windows 10, the points are allocated to provide support for one data sporadically.

**Table 1. Facebook data set statistics.**

|   | Description                       | Value    |
|---|-----------------------------------|----------|
| 1 | Edge                              | 88232    |
| 2 | Points                            | 4038     |
| 3 | Edges in largest WCC              | 88234    |
| 4 | Points in largest WCC             | 4038     |
| 5 | Edges in largest SCC              | 88232    |
| 6 | Points in largest SCC             | 4038     |
| 7 | Average clustering coefficient     | 0.6055   |
| 8 | NO. of triangles                  | 1612011  |
| 9 | Fraction of closed triangles      | 0.2648   |
| 10| Diameter                          | 8        |

The benefit is achievement of the required fraction of supporter or every data for the allocated seed point pairs. For simplicity of a tie between the organizations, a boundary of 5% is contemplated. If the contrast is lower to this boundary, then balance is attained. As shown in figure 10 in [17] illustrates the balance for the separate fraction of supporters. $p_1$ and $p_2$ are the fractions of the supporter for data 1 and data 2, separately.

### 4.2 Results for Facebook data

An illustration is made for the outcomes from the three techniques (EC,RD,DC) based on Facebook data. Being that there is existence of two aggressive data (i.e., info ‘m’ 1 and info ‘m’ 2), and three techniques for seed determination; thus, better evaluation entails further classification of the outcomes into fractions of impacted points ($\mu_{\text{influenced}}$) and the fraction of supporter points ($\mu_{\text{supporter}}$) for every data. For further evaluation, various interconnections both random and regular, apart from the Facebook dataset were also produced. More explanations are detailed in subsequent sections for the interconnection characteristics.

Here, the $x$-axis represents the quantity of levels ‘$L$’ and $y$-axis constitutes a fraction of the impacted points, $\mu_{\text{influenced}}$ or fraction of the supporter nodes, $\mu_{\text{supporter}}$. Figure 5-A, for Facebook interconnection, there is an illustration of the influence of $\mu$ with $L$ for techniques. For Facebook dataset, there is a higher influence for $\mu$ on DC in comparison with EC but like RD. The reason being the method used for choosing the seed selection earlier explained in Section 1. In observation was less variance of (DC, EC) but greater variance of (RD), which
is as a result of target size earlier described in Algorithm 4, allocated to 10%. Figure 5- B exhibits rise of $\mu_{supporter}$ over $L$ for various techniques.

The key focus of any company is the maximization of supporters. However, it is indicated that DC $\mu_{supporter}$ for both companies was similar at the endpoint. Accordingly, balance was attained. There was a higher population in favor of the information, hence Dc on Facebook interconnection is recommended. Rd was satisfactory although with maximum variance. On the contrary, EC attained balance with a lower populace in comparison to DC and RD, due to the method for choosing the seed. There is a high reduction of information during the commencement of the distribution procedure for EC. Figure 5-A reveals the integrated outcomes for all the three techniques for the fraction of influenced points ($\mu_{influenced}$) on the Facebook interconnections. From observations, for the Facebook dataset, DC and RD reveal the same characteristics with EC behaving contrary. In the end, all the techniques achieved the influence of the whole interconnections for a dataset. Figure 5-B reveals the unified outcomes for the fraction of supporter points ($\mu_{supporter}$) in the interconnections. For the Facebook interconnections, RD exhibited satisfactory outcomes in comparison to DC and EC. Also, DC outcomes were higher to EC.

Figure 5. Facebook Network.

4.1 Random Network 1 (Result)

This is an interconnection with the characteristic of having similar ends as the Facebook interconnection and nearly the same moderate degree. The Clustering Coefficient (C.C) of a random interconnection 1 is issued for contrasting within a main interconnection. C.C. is an estimate of the level to which ends in a graph tend to group together. It is of benefit to for data dissemination process. For random interconnection 1 with the same characteristics to Facebook interconnection, Figure 6-A exhibits that with few levels, the entire interconnection was influenced by data in comparison to the main network. In conclusion, the diameter of the random interconnection 1 was minimal in comparison to the actual interconnection. $\mu_{supporter}$ for data was exhibited in Fig.6-B For DC, low variance was seen, and balance was attained [25]. A similar characteristic was also exhibited by EC (Figure 6- B)).
Figure 6. Random Network 1.

In Fig.6-B, the supporter for data 1 was exhibited. For DC, a higher contrast of more than 5% margin was exhibited between the $\mu$ supporter for data. There was a greater change in EC fraction of supporter for data in comparison to the actual interconnection, because of better network diameter. This is also as a result of an adjacent seed point selected earlier by EC. The rise in level numbers results in lower support for data which is equally lower in comparison with the margin. Equilibrium attainment was due to the fewer support data in comparison to margin. The RD technique performed better for $\mu$ supporter further attaining balance. This signifies lesser number of loops in the interconnections. From Fig.6- A for (DC), there are 5 levels for influence of data, likewise for EC and RD. In summary, there was a lower diameter for random interconnection 1 in comparison to the actual Facebook interconnection. Fig.6- B shows data supporters. The balance was attained in DC; however average variance was seen. Comparably, balance was attained for (EC),(RD). The fraction of influenced points ($\mu$ influenced) in a random network 1; it was observed that (DC, EC, RD) showed similar behaviors as they succeeded in impacting the whole network. The fraction of supporter points ($\mu$ supporter), enhancement results from (RD , EC) on haphazard link1 having same elements for Facebook links.

4.2 Random Network 2 (Result)

Random network 2 similarly entails characteristics like the random interconnection 1. For random interconnection 2 similar characteristics were for the Facebook interconnection. Exhibited in Figure 7-A is that for DC, the whole interconnection was impacted by data in four parts. Five levels were undertaken by EC while four for RD. In conclusion, Facebook's interconnection had greater diameter in comparison to RD.

Figure 7-B exhibits $\mu$ supporter for data. For DC, there was low variance, with balance achievement. Similar behavior was seen in EC. For RD, there was average variance with achievement of symmetry.
4.3 Regular Network (Result)

This is a random interconnection having about the same moderate level of the actual interconnection (Facebook). It helps in bringing out the benefit of level dissemination of points in an interconnection. For a regular interconnection possessing equivalent factors to Facebook interconnection, the fraction of impacted points are revealed in figure 8-A. There was lower influence of the total populace impacted by data for DC. This was the same for EC and RD as in figure 8- A. On the other hand, figure 8-B highlights the fraction of supporter ends. Less μ supporter and moderate variance were exhibited for DC yet balance was attained. Generally, satisfactory outcomes were revealed by RD in comparison to Dc and EC. Providing better explanation. For the benefit of topological loops (an interconnection factor).

![Figure 8. Regular Network](image)

Differentiating Facebook internetwork outcomes with outcome 2 gave the benefit of topological loops. There were few supporters for random normal interconnection showing the benefit of network disseminations for diffusion.

5. Conclusion

In environment of social media, the competitive advantage for commercial products was used widely. The enterprises want to scatter details for their products so that they are known widely in social media. This is because they believe in competitive advantage for commercial products. In this study, two parameters are selected (1) Clustering Coefficient(C.C); and (2) Degree (level) distribution for stations (points) in order to comparison outcomes. each of techniques (DC, EC, RD) which has been used is vary from one other. The distinguishing factor was on the seed point determination technique, directly dependent on the interconnection structure. Thus, the distinctness was as a result of one, seed picking technique, and two, interconnection structure values i.e., (C.C) and degree (level) distribution of point. In addition, the comparison, topological loops are beneficial for changes, however seed determination techniques may fail to perform. The degree of distribution arising from comparison of random and random normal interconnections proved significant for changes. Data sets outcomes distinction revealed a better outcomes for total fraction points support. Moreover, symmetry was obtained for the fraction of point support. The Dc exhibited this factor because of its priority for point level for seed choosing. The Rank degree technique gives priority for the interconnection splitting for seed determination. The aim of this study is finding an initial common ground the dissemination to social platforms and fast data diffusion can be done. The evaluation is also accomplished on the number of fraction parts in various sections are affected by the different rates of data diffusion. The simulation result for proposed framework introduces better outcomes result. The technique performed uniformly well and exhibited preferred outcomes in comparison with the other two techniques.
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