Course Project Report

Identifying Key spreading nodes using entropy-driven gravity model

Submitted By

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Dr. Sowmya Kamath S, Dept of IT, NITK Surathkal

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<u>**C E R T I F I C A T E**</u>

This is to certify that the Course project Work Report entitled **"Identifying influential spreaders by a gravity model"** is submitted by the group mentioned below -

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Name of the Student	Register No.	Signature with Date
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this report is a record of the work carried out by them as part of the course **Web and Social Computing (IT752)** during the semester **Jan-Apr 2023**. It is accepted as the Course Project Report submission in the partial fulfillment of the requirements for the award of the degree of **Master of Technology in Information Technology.**

Dr. Sowmya Kamath S.

DECLARATION

We hereby declare that the project report entitled **"Identifying influential spreaders by a gravity model"** submitted by us for the course **Web and Social Computing (IT752)** during the semester **Jan-Apr 2023**, as part of the partial course requirements for the award of the degree of Master of Technology in Information Technology at NITK Surathkal is our original work. We declare that the project has not formed the basis for the award of any degree, associateship, fellowship or any other similar titles elsewhere.

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Identifying Key spreading nodes using entropy-driven gravity model

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Abstract— **It is still difficult to pinpoint prominent spreaders in the field of network research. As a result, it has attracted considerable interest from both computer science and physics communities, leading to the creation of several algorithms to address this issue. To assess the spreading potential of nodes, degree centrality, a widely utilized neighborhood-based centrality, was proposed among these methods. Nevertheless, degree centrality frequently gives too many nodes the same value, leading to a resolution restriction that makes it difficult to identify real node impacts and impairs the algorithm's ranking effectiveness. Similar to this, this problem also affects the k-shell decomposition method. We may combine a high-resolution,index that incorporates degree centrality with the k shell decomposition technique to solve the resolution limit issue. Additionally, we may obtain a better gravity model to gauge node significance in propagation dynamics by combining the suggested index with the well-known gravity law. By using Kendall's rank correlation and monotonicity value metrics, our experimental findings were contrasted with those of other cutting-edge techniques. Also, we provided the implementation of entropy using the specified gravity technique and compared it according to the same criteria.**

Keywords: **Influential spreaders, Gravity model, Ranking efficiency, Entropy rank method, Node influence**

I. INTRODUCTION

The significance of complex network research has grown in recent years as many real-world systems can be modeled as networks comprising interconnected nodes. Examples include social networks, transportation networks, biological networks (Barabási et al., 2011), and many others. One Finding influential spreaders—nodes that have a considerable influence on the transmission of knowledge, illness, or other behaviors in the network—is a significant challenge in the investigation of complex networks.

Only structural data (Lü et al., 2016), which may be broadly categorised into two clusters: path based and neighborhood based centralities, are used in the majority of current algorithms for identifying influential spreaders. The H-index, K-shell decomposition approach(Kitsak et al., 2010), and Degree centrality are a few examples of centralities(CC). and proximity centrality are two examples of path based neighborhood based centralities llike Betweenness centrality (BC)

Most current methods for finding influential spreaders depend solely on structural data , which may be generally divided into two groups: neighborhood-based centralities and path-based centralities. Examples of neighborhood-based centralities include Degree centrality (DC), H-index and k-shell decomposition method (KS) . Meanwhile, path-based centralities include closeness centrality (CC) and betweenness centrality (BC).

The identification of influential spreaders has many practical applications, such as in public health, marketing, and social media analysis. One approach to this problem is to use gravity models, which are based on the idea that the spread of information or disease in a network can be modeled as a physical force between nodes. The fundamental tenet of the gravity model is that a node's degree determines the likelihood that it will spread disease to its neighbors (i.e., the total amount of edges it contains).

However, basic gravity model (Ma et al., 2016) has limitations, as it does not take into account the fact that some nodes may be more central or more influential than others, even if they have the same degree. This is because the spread of information or disease may depend not only on the number of connections a node has, but also on the quality or strength of those connections.

To address this limitation, an improved gravity model with entropy has been proposed, this considers both the entropy (Guo et al., 2020) and degree of each node. According to the distribution of distances among two nodes and every rest node in the given network, the entropy of a node is a measurement of their centrality or impact. Nodes with high entropy are more central and influential than nodes with low entropy.

In this context, this approach has been shown to outperform the basic gravity model in identifying influential spreaders in various types of networks, including social networks and transportation networks. In this way, the improved gravity model with entropy is a useful tool for analysing or forecasting the changing behavior of complicated networks.

II. LITERATURE SURVEY

A difficult problem with many practical applications is finding influential spreaders in complicated networks. Several techniques, including degree centrality, betweenness centrality, k-shell decomposition, and eigenvector centrality, have been suggested over time to address this issue. However, these algorithms have their limitations, including resolution limitation, computational complexity, and sensitivity to network topology.

A high-resolution index that combines entropy based, degree centrality, and k-shell decomposition has been presented as a solution to these problems. This index overcomes the resolution limit problem by considering the influence of nodes within their respective local neighborhoods. A new gravity model has also been developed based on this index to quantify the significance of nodes in propagation rates.

The enhanced gravity model beats most state of the art techniques when it comes of ranking effectiveness and efficacy, according to experimental results on 4 real-world networks. In particular, it has higher ranking efficiency as determined by the monotonicity value and Kendall's rank correlation metrics.

(Yang et al., 2021) presented a new node local centrality metric for finding significant nodes in complicated networks. This index measures node influence depending on their position in the network, with diminishing effect as distance from other nodes rises. It is based on a mix of network embedding and network neighborhood topological information. On eight real-world networks, the authors assess the effectiveness of their proposed strategy to five other popular centrality techniques. The findings demonstrate that the proposed node local centrality algorithm outperforms the other methods and has applications in the study and control of information propagation in complex networks.

(Li et al., 2019) introduces an approach for finding influential nodes using gravity model. With uses some weight as mass between two nodes and ratio to square of the distance between them. Takes into account both the distance between nodes and their relative attractiveness, which can provide a more accurate measure of node influence. The gravity model is sensitive to parameter settings, which can affect the accuracy of the results. Therefore, the choice of parameters requires careful consideration and calibration.

The network's total influence is determined by both the capacity of other nodes to participate to it and the effect of each individual node. (Sheng et al., 2020) present a unique strategy for finding important nodes in complicated networks that takes into account both global and local network architecture. Using experiments on eight real-world networks, the SIR model, and Kendall's ranking correlation coefficient, the correctness of the algorithm ranking and the effect of each node on propagation were determined. When compared to alternative centrality measures such as closeness, betweenness centrality, and H-index, the data imply that this technique can more reliably and successfully identify influential nodes. Despite our technique's great temporal complexity, we hope to refine it in future work so that it may be used to a broader range of networks.

The paper (Wang et al., 2022) mainly describes a method for building models that may be used to identify prominent nodes based on the entropy of those nodes, which is determined by the weight distribution of the connections that link them. Furthermore, discussed are the processes for evaluating node effects and temporal complexity. The validation of the experiments is carried out in four stages: case test, consistency analysis, correlation analysis and transmission capacity. They picked eight real world networks with varying network structural qualities. The outcomes of the experiments show that the suggested algorithm, LENC, offers a number of advantages. Nevertheless, Simply the vertices' the initial and the second order edges are considered when computing the effect of nodes in order to limit the time complexity of computation expenses. As a result, there is still much space for improvement in node influence ranking accuracy, and the algorithm will be enhanced in further work.

(Li et al., 2021) outlines a generalised gravity model for identifying major spreaders that takes into consideration both of them the weight on the edges and the local clustering coefficient. The proposed model can be degenerated into a traditional gravity model when the parameter alpha equals to 0. Experiments across four real world networks revealed that the proposed method outperforms the gravity model and weighted gravity model, and is effective in capturing the local information of nodes. There are still some challenges to sort out, such as when to apply the general gravity model to weighted systems and how to select the appropriate alpha value. Future research will concentrate on improving approaches for identifying influential propagators based on the gravity formula.

(Li and Xiao, 2021) outlines the EGM as a unique technique for finding significant spreaders in intricate networks using accurate radius and value data. The precise measurement of the effect radius and the impartial choice of node mass are the two main contributions of this approach. EGM calculates the range of interaction between gravity force for influence radius, which resolves the issue of the gravity-based model's imprecise truncation radius. To fully assess the impact of neighboring nodes, which might yield value information about a node, the EGM includes information entropy for mass selection. In this study, EGM is compared with classical methods such as DC, BC, PC, CC EC, similar methods such as WGC, GGC, GC, and state of the art measures such as LID and FLD through six different experiments on eleven real world networks. The findings demonstrate that EGM surpasses the other approaches for locating critical spreaders in complex networks in terms of efficiency and stability.

III. METHODOLOGY

This section comprehensively explains the functions of the algorithms employed for node influence ranking. Firstly, we utilize the SIR model (Hethcote, 2000) to derive the initial rank. Subsequently, we incorporate the entropy of nodes and their corresponding k shell ranks using the gravity model to obtain the final rank. Finally, we evaluate the obtained rank against the SIR rank using the Kendall's tau (Kendall, 1938) function. The following is an overview of the methodologies implemented in this project.

A. SIR Model

The population is divided into three groups under the SIR model: susceptible (S), infected (I), and recovered (R). According to the concept, people in the population can only transition from being vulnerable to becoming infected and from becoming infected to recovering. where S represents the number of sensitive individuals, I represent the number of infected people, and R represents the number of people who have recovered. β is the transmission rate, this indicates the likelihood that someone who is vulnerable will become infected when they come into touch with an infected person. γ is the recovery rate, it reflects the pace at which those who are infected recover and develop disease immunity.

The SIR model assumes that the transmission or infection rate β and the recovery rate γ are constant throughout the outbreak. This assumption allows the model to make predictions about the future course of the outbreak based on the initial conditions.

The SIR model can be used to predict the number of individuals who will be infected and recovered over time, as well as the peak of the outbreak and the duration of the outbreak.

B. Entropy

The degree of randomness or heterogeneity in a graph is determined using entropy. Entropy can be used to describe the distribution of nodes, edges, or other properties of the graph, and can be used to identify anomalous or interesting patterns in the graph.

Shannon entropy, a concept from information theory, is frequently used to calculate entropy in graphs. The probability distribution of nodes or edges in a graph is an example of a random variable whose quantity of information or uncertainty may be measured using the Shannon entropy.

The probability distribution of the nodes or edges can be calculated before calculating the Shannon entropy in a graph. This can be done by counting the number of occurrences of each node or edge and dividing by the total number of nodes or edges, respectively.

Once we have the probability distribution, we can calculate the Shannon entropy using the following formula:

$$H = -\Sigma p(i) * \log_2 p(i)$$

where H is the Shannon entropy, p(i) is the probability of the i^{th} node or edge, and log is the base 2 logarithm.

The Shannon entropy ranges from 0 to log2(N), where N is total number of nodes or edges in the given graph. A value of 0 indicates that the probability distribution is completely certain or uniform, while a value of log2(N) indicates that the probability distribution is completely uncertain or random.

In graph theory, high entropy can indicate a high degree of diversity or heterogeneity in the distribution of nodes or edges, while low entropy can indicate a low degree of diversity or homogeneity. Entropy can be useful for characterizing the structure and organization of a graph and for identifying anomalous or interesting patterns.

Entropy is a useful measure for understanding the structure and behavior of complex systems, including graphs, and has a wide range of uses in the study of information theory, physics, and computer science.

C. K-shell Rank

Based on the number of other nodes it is associated to that also have a high degree of centrality, K shell centrality evaluates a node's significance in a network.Nodes with high k shell centrality are situated inside the network's innermost shells and are linked to nodes with high degree centrality. K shell centrality can be used to identify nodes that are both well connected and have a high degree of influence in the network. It can also be used to evaluate the hierarchical structure of the network.

D. Monotonicity

The term "monotonicity" (Mr) (Bae and Kim, 2014) is a metric that we use to evaluate how well an algorithm generates a ranking list. This statistic assesses how distinctive a ranking list's components are. In other words, it establishes if and how many ties there are in the ranking. A ranking is said to be monotonic if there are no ties, meaning that all elements in the list are unique and in a strict ordering. The more monotonic a ranking is, the more accurate and reliable it is considered to be.

$$M_r(L) = \left[1 - \frac{\sum_{r \in L} N_t(r)(N_t(r) - 1)}{N(N-1))}\right]^2$$

The rank list L denotes the order of the items, while Nt(r) refers to the count of ties that have the same rank r.

E. Gravity model

The gravity model is a mathematical model used to predict the flow of information or influence between nodes in a network, based on their size and distance. The entropy and k shell value are two additional measures that can be used to enhance the accuracy of the gravity model.

Entropy, as mentioned before, measures the degree of randomness or heterogeneity in the distribution of nodes or edges in a graph. In the context of the gravity model, entropy can be used to weight the nodes based on their diversity or heterogeneity, which can help to capture more accurately the patterns of flow within the network.

K shell value, on the other hand, is a measure of the structural importance of nodes in a graph. High k shell nodes are ones that are linked to a lot of other nodes that also have a lot of high k shell nodes. To find the most important nodes in the network, k shell value may be utilized in the gravity model context to weight the nodes according to their structural relevance.

Combining the gravity model with entropy and k shell value can result in a more accurate prediction of the flow of information or influence between nodes in the network. By weighting the nodes based on their diversity and structural importance, the gravity model can better capture the patterns of flow within the network, and identify the most influential nodes that are likely to have the greatest impact on the system as a whole

We'll take mass of a node as sum of k shell value and entropy of a node.

$$M(i) = e(i) + ks(i)$$

Then we'll apply gravity model as following equation. Where R is the truncation radius. We should consider nodes around i which are not far more than distance of R. A modest value of R is recommended for most real world networks as they typically exhibit small world properties. Generally, a value of 2 or 3 can be set for R. In this experiment, we have considered R is equal to 3.

$$\text{Novel GM(i)} = \sum_{i \neq j, d(i,j) \leq R} \frac{M(i) * M(j)}{d^2(i,j)}$$

Where d(i,j) means distance between node i and j. which should be less than R.

For example, if we are analyzing a social network and using the gravity model with entropy and k shell value, we may find that certain nodes with high entropy and high k shell value are the most influential in terms of information flow. This information can be used to target marketing or advertising campaigns towards these nodes, or to identify key opinion leaders within the network.

By Algorithm 1, we can understand calculation of the suggested gravity model.

Algorithm 1: Novel gravity model

```
Input: graph: G<V,E>, truncation: R, number of nodes: N
Output:Rank[v,NovelGM(v)]
For i ← 1 to N do
        H = −Σp(i) ∗ log2 p(i)
End
For i ← 1 to N do
        For i is neighbour of j
                E(i)  += H(j)
        End
End
K ← 1
While !isEmpty(V) do
        q(k) ← 0;
        repeat
                q(k) ←q(k) + 1
                Find all nodes in G with degree k;
                For such node v with degree k do
                        Ks(v)←k;
                        P(v)←q(k);
                        Remove node v from G;
                End
        Until All remaining nodes in G have degree > k ;
        K ← k + 1;
End
q_max ← max q(k);
For i ← 1 to N do
        For j ←1 to R
                NovelGM(i) +=  (E(i)+ks(i)) * (E(j)+ks(j))/d²(I,j) ;
        End
End
```

The combination of the gravity model with entropy and k shell value can provide a more nuanced and accurate understanding of the flow of information or influence within a network, and can be employed in a wide range of applications at the same time including social network analysis, marketing, and opinion polling.

IV. EXPERIMENT AND RESULT

This section describes the experiments we carried out to assess the performance of our suggested algorithm. On a set of benchmark datasets, we compare its findings to those of current algorithms and present a comprehensive analysis of the experimental results.

A. Dataset Detail

We have used 4 network datasets. Given table shows basic characteristic of given dataset of networks.

The paper examines various network characteristics, such as the number of nodes (V), the number of links (E), the average degree <k>, the average distance <d>, and the epidemic threshold (βc) of the SIR model.

TABLE I: 4 NETWORK'S FEATURES

Network	V	E	<k>	<d>	βc
Email	1133	5451	9.6222	3.6060	0.0565
PB	1222	16714	27.3552	2.7375	0.0125
Router	5022	6258	2.4922	6.4488	0.0786
Facebook	4039	88234	43.6910	3.6925	0.0095

B. Result

In Table II, we compared with 4 classic methods i.e., DC (Degree Centrality), CC (Crossness Centrality), BC (Betweenness Centrality) and KS (K Shell ranking).

First of all, we'll find rank of nodes by SIR model, which then used for comparing with all these methods. SIR rank is taken as standard rank. Where β (infection rate) is taken equal to βc (epidemic threshold) of respective network and recover probably is taken as 1.

TABLE II: KENDALL'S TAU COMPARISON WITH CLASSIC METHODS

Network	DC	BC	CC	KS	Novel GM
Email	0.30602	0.26228	**0.32427**	0.31948	0.31066
PB	**0.05002**	-0.01320	0.02302	0.04018	0.01389
Router	0.05631	0.06071	0.01225	**0.07125**	0.00621
Facebook	0.02789	0.00361	0.01094	**0.03425**	0.00594

In below table III, we have compared novel gravity model with other Gravity model like DKGM (DK based gravity model), GC (Gravity Centrality)(Ma et al., 2016) and LGM (Local Gravity Model)(Li et al., 2019).

TABLE III: KENDALL'S TAU COMPARISON WITH GRAVITY MODEL

Network	DKGM	GC	LGM	Novel GM
Email	0.31392	0.31015	**0.31265**	0.31066
PB	0.01686	0.01037	**0.05909**	0.01389
Router	-0.0028319	0.00345	-0.002346	**0.00621**
Facebook	**0.01591**	0.01370	-0.03038	0.00594

By observing both resultant tables, we can see novel gravity model varies from network to network. It is not giving consistent accuracy. For network Router, Novel Gravity Model is providing more accuracy than rest Gravity based models. This can be because of more number of nodes present in the network. Router network has less average degree, that shows spars graph which also could be possible reason.

C. Monotonicity

Table IV and V shows monotonicity given be each method. Which indicates the uniqueness of the elements in a ranking list. More monotonicity more it is providing unique ranks for each node.

TABLE IV: MONOTONICITY COMPARISON WITH CLASSIC METHODS

Network	DC	BC	CC	KS	Novel GM
Email	0.88736	0.94000	0.99880	0.80881	**0.99990**
PB	0.93284	0.94890	0.99797	0.90636	**0.99939**
Router	0.28861	0.30379	0.99607	0.06913	**0.99736**
Facebook	0.97390	0.98552	0.99667	0.94192	**0.99992**

TABLE V: MONOTONICITY COMPARISON WITH GRAVITY MODEL

Network	DKGM	GC	LGM	Novel GM
Email	0.99989	0.99989	0.99989	**0.99990**
PB	0.99961	0.99927	0.99930	**0.99939**
Router	0.99712	0.99668	0.99691	**0.99736**
Facebook	0.99987	0.99980	0.99987	**0.99992**

As we can clearly see, monotonicity of novel model is high most of the time, which means rank is uniquely distributed in the system.

D. Kendall's Tau for different β

Let's compare Kendall's Tau with different infected rate for all four network and observe the behaviour of result.

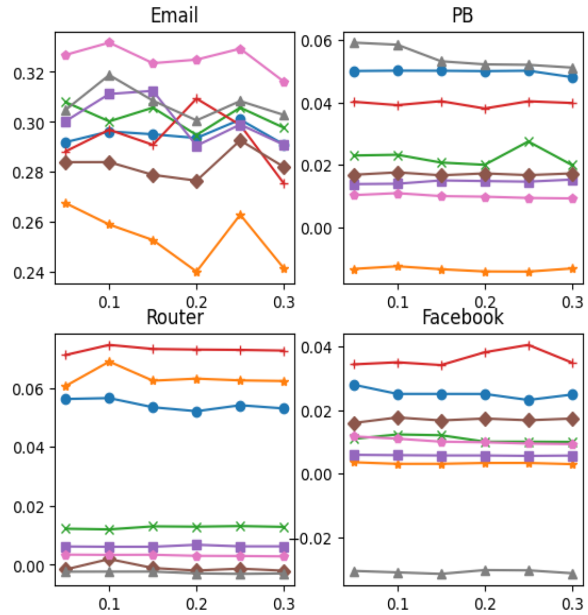

Fig. 1: Acccuracy measurement with different β

Where line with circle is DC, * is BC, X is CC, + is k shell, Square is new gravity model, diamond is base gravity model, pentagon is GC and triangle is LGM.

As it is mentioned in Fig 1, changing in β is not affecting the accuracy of the different algorithms. it is not varying much.

E. Effect of changing radius in Gravity Model

Truncation radius in gravity model plays important role. we have to decide radius very carefully. the accuracy may vary as R changes. R is generally should be small, it can be set to 2 or 3. In our experiment, we have selected at 3. We also have compared with R=5 and compared the result(accuracy) with R=3. We have seen that accuracy is decreasing.

TABLE VI: KENDALL'S TAU COMPARISON WITH DIFFERENT R

Network	R=3	R=5
New Gravity	0.31066	0.29498
Base Gravity	0.31392	0.29432
GC	0.31015	0.29468
LGM	0.31265	0.29751

Table VI is describing Kendall's tau with R=2 and R=5 for Email Network. With R=5, the accuracy of Kendell's Tau is decreasing, hence we can say that with increase in value of R, the accuracy is decreasing, inversely proportional.

V. CONCLUSIONS

In conclusion, the goal of our study was to locate significant spreaders in complicated networks by employing a gravity model that takes into account node entropy. While the proposed method showed promising results in some cases, it did not consistently outperform other established methods. As observed in Table III Router Network is giving high accuracy compare to other gravity model, which concludes that Novel Gravity Model can perform better with less average degree and high average distance network. The level of accuracy achieved may also be dependent on other factors such as network type or other parameters. Therefore, further research is needed to optimize the proposed method and identify its strengths and limitations in various network contexts Overall, our analysis makes a positive contribution to the continuing endeavor to create better techniques for locating influential spreaders in complicated networks.

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