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Link Prediction in Social Networks using Vertex Entropy

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***Abstract:** Many link prediction methods have been put out and tested on several actual networks. The weights of linkages are rarely considered in these studies. Taking both the network's structure and link weight into account is required for link prediction. Previous researchers mostly overlooked the topological structure data in favour of the naturally occurring link weight. With the use of the concept of entropy, a new link prediction algorithm has been put forth in this paper. When used in real-time social networks, this algorithm outperforms the industry standard techniques. This paper concentrated on both topological structural information which focuses on calculating the vertex entropy of each very vertex and link weight in the proposed method. Both weighted and unweighted networks can benefit from the proposed method. Unipartite and bipartite networks can also use the suggested methods. Further, results demonstrate that the proposed method performs better than competing or traditional strategies, particularly when targeted social networks are sufficiently dense.*

***Keywords:** Ego Network, Social Network, Link Prediction, Sociogram.*

I. INTRODUCTION

Social networks play important role in understanding the nature of human behavior as well as entities. With millions of users actively participating in one or more online social networking sites, research into social networks has gained a lot of attention. Social networks are a rich source of data that can be mined or examined to get useful conclusions. Researchers from a variety of fields, including biologists, anthropologists, and data scientists to mention a few, are exploring the study of social networks as a major scientific subject of study. Scientists from a variety of professions have shown a great deal of interest in social link network analysis. Nodes (individuals or organizations) in a social network are connected by many sorts of interactions. A social network consists of various social actors, or nodes (such as individuals or organizations), and various dyadic links that link these nodes together.

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For instance, experts in a field of study, employees in a company, and Business executives in major companies can be compared to nodes in a network, and coauthors of papers, people working on a project, and board members can be compared to edges. The purpose of social networks is to provide chances for networking, information sharing, and company promotion.

A. Problem Statement: Social networks are highly dynamic, sparse, and collectively structured, making it difficult to predict their outcomes. The task of accurately predicting the existence of links or connections in a domain is both an important task and a very difficult task.

So, is it possible to predict more with social media? Because connections from networks, their maintenance, and their quality reflect individuals' social behaviour, their studies provide both quantitative and qualitative insight into human relationships which are useful for evaluation. Chain prediction also has broad applications in fields such as bibliography, molecular biology, forensics, and recommendation systems The topological structure of a social network is represented by an unweighted, undirected graph with "V" representing the vertices and "E" representing the set of edges, where e = (u,v) € E indicates an interaction between u and v that happened at a specific time t(e).

Input: A graphical structure of the complex social network

Output: Edges with the prediction score are a group. The prediction score displays the likelihood that an edge will occur. A higher prediction score denotes a strong likelihood that an edge exists. Graph G at time "t1" is used as the input for the link prediction algorithm, which then forecasts the potential future connection at a time "t2". The expected linkages are depicted in Graph G′ by the dotted line.

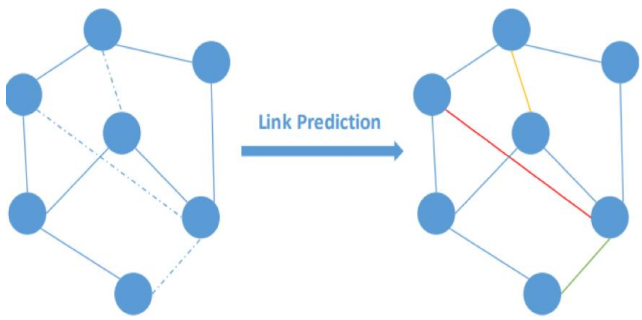

Fig. I. Link prediction in the social network.

Social Network: In a social network graph, the nodes stand in for people, while the edges, or connections between nodes, reflect social ties between them, such as friendship or teamwork on a project.

A. Social Network Analysis: A social network is made up of a group of people and the connections between them. These connections are examined by social network analysis to define people and groups as elements of a social structure [12]. People communicate with one another, and the patterns of these interactions provide information about the individuals involved. Relationships allow knowledge to spread throughout a network, allowing one person to have an impact on another. The key distinction between social network analysis and other methodologies is the significance of the related information. The study unit is a dyad made up of two people and their relationships, as opposed to concentrating on each individual independently. **Sociograms (A sociogram is a graph database that shows connections between group members to represent the group's social network)**, in which nodes are represented as points and links are depicted as lines, are frequently used to display these networks. By modifying the visual portrayal of a network's nodes and edges, these visualizations give a means to qualitatively analyze networks.

B. Types Of Social Networks: There are two broad categories for online social networks 1) certain or 2) uncertain. In an uncertain network, link prediction probabilities are connected to node-node interaction, however, in some types, there are no probabilities connected to node-node interaction, which is the link between the nodes. These certain and uncertain online social networks are further divided into static and dynamic social networks, with dynamic social networks further subdivided into incremental, decremental, and mixed social networks.

1. Static Network: The networks are depicted by nodes that are linked together by edges. Static network nodes never change their position or fail. The sides or links continuously maintain their operating status [15]. The network's overall structure will not change. For instance, a social network instance at a particular time will be a kind of static network. In contrast to certain static networks, uncertain static networks have edges that are likely connections between nodes.

2. Dynamic Network: Online dynamic social networks [16] alter their structure with respect to time.
   a. There might be more or fewer nodes in the network over time, making them visible or invisible (also known as a stochastic network).
   b. The overall Node count is fixed, only the edges experience crashes and recover appropriately.
   c. The network has a constant total number of nodes, but when new links are established between them over time, the network develops and the nodes' positions change as a result.

C. Introduction to proposed Method: Entropy [13] is a tool that is used by most researchers to study complex networks. This paper aims to propose an algorithm (SVE) that calculates the vertex entropy of every vertex of real-world networks.

Ego network: Ego networks consist of the focal node known as the "ego," the nodes it is directly connected to (known as the "alters"), and any connections that may exist between the alters [14].

II. CHARCTERSTICS OF SOCIAL NETWORK

- *Small world effect*: This phenomenon occurs when a network's average distance is particularly modest in relation to its overall size. This means that in a network, every pair of nodes can be connected by a short path. In his well-known studies, Stanley Milgram asked participants to send postcards only through their close friends in order to a predetermined recipient. Depending on the sample size, Milgram discovered that there were often between 4.4 and 5.7 intermediaries in the course taken by the postcards. Facebook has today released the findings of its first global social network graph distance computation, which was conducted using the complete Facebook network of active members (721 million users, 69 billion friendship links).
- *Scale-free effect:* Most of the nodes have very few links in the network, and only some of the nodes have lots of links. In such type of network nodes having lots of links are referred to as “Hubs” this node controls the functionality of the network. This effect demonstrates that the degree distribution of nodes in the large-scale network is substantially unbalanced.
- *Clustering effect:* This effect is described by the concept that there are a lot of fully connected subgraphs in a graph of a social network.

III. MOTIVATION

The number of common neighbours between the nodes represents the similarity between the nodes and has a link between the nodes. Examining the common neighbours is a simple method but on other hand, this method suffers from low accuracy. After surveying various articles that rely on first-order neighbours the following points were observed:

1. The nodes connected by a substantial portion of links in real-world networks might not have any neighbours in common. This could be a large amount, by cursory analysis of the nine networks represented in a graphical manner.

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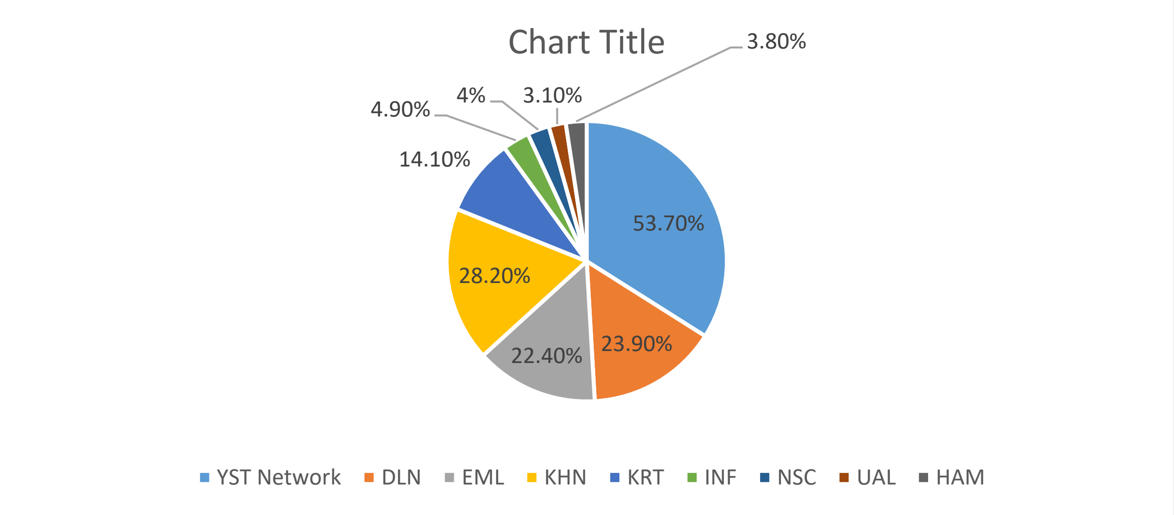

Fig. II. Analysis of networks might not have any neighbours in common.

2. There is a significant overlap between the nodes when all existing links are sorted. Moreover, with the same number of neighbours, all speculative ties that might form between nodes without links, are ordered by frequency. The above-mentioned points drive the study in this paper.

IV. TRADITIONAL ALGORITHMS

Similarity-based algorithms have been famous in the field of link prediction in recent years due to their simple structure. A score is given based on how similar two unconnected nodes are, and a higher score denotes a higher possibility of their existence. Most of the similarity indices, including Common Neighbors and Shortest Path Distance, are derived from network structure. In surveys of link prediction, there are at least 20 similarity indexes. A common metric for link prediction in social networks is the similarity-based index derived by network topology, despite some criticism of its drawbacks. Further in this section, some simple and commonly used topological measures are discussed.

1. Neighbourhood base measures (Local similarity-based metrices)

A. *Common Neighbours (CN):* The most basic and widely used metric measures the neighbourhood overlaping between the two nodes x and y [1]. The mathematical definition of common neighbours CN(x,y) is given as*:*

$$CN\ (x, y) = |\Gamma(x) \cap \Gamma(y)|$$

Where Γ(x) is the set of neighbours of x and Γ(y) is the set of neighbours of y.

Applications:

B. *Jaccard Coefficient (JC):* By taking into account the total number of shared and non-shared neighbours, the Jaccard index [2] normalises the size of common neighbours. The value of the Jaccard Coefficient (JC) is as:

$$JC\ (x, y) = \frac{|\Gamma(x) \cap \Gamma(y)|}{|\Gamma(x) \cup \Gamma(y)|}$$

Where Γ(x) are x's neighbours and Γ(y) are y's neighbours.

C. *Adamic Adar (AA):* The Adamic Adar [3] Common neighbours with a low degree are given more importance by this measure. It is calculated as the two nodes' combined inverse logarithmic degree centrality of their neighbours.. Adamic Adar is given as:

$$AA\ (x, y) = \sum_{z \in \Gamma(x) \cap \Gamma(y)} \frac{1}{log(|\Gamma(z)|)}$$

With neighbours of lower degrees given more weight in the formulation, Adamic Adar connects node pairings that have at least one common neighbours.

D. *Resource Allocation (RA):* Instead of using a logarithmic number, the Resource Allocation employs the degree magnitude. The shared neighbours of x and y are also connected by a means that transmits or distributes resources from x to y, and this medium equally distributes resources to all of the neighbours. The similarity between x and y is measured by the quantity of resources y receives from x [4]. Resource Allocation (RA) is given as:

$$RA(x,y) = \sum_{z \in \Gamma(x) \cap \Gamma(y)} \frac{1}{|\Gamma(z)|}$$

2. Path-based measures (Global similarity-based metrics)

A. *Katz (KZ):* This metric [5] computes the Sum of paths with lengths between 2 and a specified higher path length between nodes x and y. To address and solve the problem of increasing lengths of paths which causes weak information flow between the nodes. Katz's measure, which employs a damping factor with a value between o and 1, is put into action to damp the longer pathways. Katz is given as:

$$KZ\ (x, y) = \sum_{l}^{L} \beta^{l} |Path_{l}\ (x, y)|^{l}$$

path (x, y) consists of homogeneous edges of length l between x and y.

B. *Sim Rank (SR):* Two nodes are similar if they are related to other similar nodes, according to the Sim Rank [5]. Sim rank is given as:

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$$\text{SIM}(x, y) = \beta \frac{\sum_{a \in \Gamma(x)} \sum_{b \in \Gamma(y)} SIM(a,b)}{|\Gamma(x).\Gamma(y)|}$$

Where β is damping factor with $0 < \beta < 1$ and SIM (x, x) = 1.

3. *Random-Walk base measure*

A. *Hitting Time (HT)*: This is a random walk measure, which starts from a node let's say x, and recursively moves to a random neighbour of x. Hitting time [6] is the expected number of steps required for a random walk starting from x and ending at y.

B. *Average commute time (CT):* In Average commute time [7] random walks from x to y and vice versa are added. Average Commute Time is a symmetric metric.

$$\text{CT}(x, y) = -(\text{HT}(x, y) + \text{HT}(y, x))$$

C. *Page Rank:* Based on the importance of nodes that are nearby, Page Rank [8] describes the importance of node x in the network. Page Rank is given as:

$$\text{PR}(x) = \frac{1-\alpha}{\text{M}} + \sum_{z \in \Gamma(x)} \frac{\text{PR}(z)}{|\Gamma(z)|}$$

Where M is the total number of edges in G

- Additionally, if in case it is found that none of the single measures works equally well for all the datasets. Therefore, a supervised framework is proposed by Mohammad Al Hasan [9] where the strength of all these measures can be effectively utilized. The supervised framework for link prediction thus proposed performs the following the steps

1. Extracting the learning instances from the social network.
2. Training set and a test set are then created from the retrieved instances.
3. Features and class labels are computed for training as well as test instances.
4. Further, a classifier is trained on obtained features, and class labels are processed through the classifier.
5. Labels are predicted from the trained classifier.

- *Time Complexity:* These algorithms differ in time complexity.
    - a) Common Neighbours (CN) - O(n^2).
    - b) Jaccard Coefficient (JC) - O($2n^2$).
    - c) Adamic Adar (AA) - O($2n^2$).
    - **d)** Resource Allocation (RA) - O($2n^2$).

V. LINK PREDICTION IN WEIGHTED SOCIAL NETWORK

- A network that has weights assigned to the links connecting its nodes is said to be weighted. In dense social networks as well as open and dynamic online social networks, Murata el al. [10] novel algorithm is particularly useful. Weighted graph proximity measurements were proposed by the authors as novel network proximity metrics. This variable enhances link prediction performance in complicated networks. This method is predicated on the idea that in a complex network, both the weights of an existing edge and the proximity parameters can improve prediction accuracy. The weight of edges is used to calculate the weighted CN, weighted Adamic/Adar, and weighted preferential attachment score. Here is how the weighted PA score is calculated:

$$Weighted_{\ Score}(\text{i, j}) = \sum_{x' \in \Gamma(x)} w(x, x') \cdot \sum_{y' \in \Gamma(x)} w(y, y')$$

  The model was tested by the authors on a Question-Answering Bulletin Boards (QABB) dataset and found promising results.

- Three similarity metrics were utilised by Lu et al. [11] Common Neighbour, Resource Allocation, and Adamic-Adar score. They thought of using the weak ties hypothesis to forecast links. The weak tie hypothesis states that networks are dependent on linkages with low weights. The impact of weak ties on link prediction was utilised using a free parameter. Using a free parameter, the effect of weak ties on link prediction was taken into consideration. The experimental findings demonstrate that weak relationships have a significant impact on link prediction.

VI. RESEARCH GAP

The following study gaps were identified in the field of Link prediction after reviewing the numerous research studies included in the literature review.

1. Link prediction has been the subject of numerous algorithms, but due to the complexity and diversity of real-world situations, it remains difficult to predict linkages in complex networks accurately and effectively. Algorithm prediction performance needs significant improvement in terms of AUC and Precision.
2. Many mathematical ideas and network characteristics, such as vertex entropy, and the centrality of complex networks are still not employed to determine whether two nodes are comparable to one another. These ideas are important and can be used to determine whether two nodes are comparable. Additionally, there are numerous real-world uses for these ideas and similarity scores, including link prediction.
3. Because real-world occurrences are so varied, modelling them requires a variety of networks. One algorithm does not perform well on all types of networks, but numerous methods are typically available to cope with these various networks. There is not a single method that can predict links on all types of networks, including unweighted, weighted, unipartite, bipartite, and multiplex networks, effectively.

VII. PROPOSED METHOD

In weighted networks, the proposed algorithm for link prediction is the "sum of vertex entropy". The suggested method mainly concentrates on networks that are made up of a focal node termed "ego," the nodes it is directly connected to (referred to as "alters"), and any relationships that may exist between the alters and the Node entropy of the graph. The algorithm primarily operates in the manner described below.

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1. Recognizing ego networks.
2. Calculating the Probability mass function(pmf).
3. Calculation of vertex entropy.
4. Calculation of the SVE score.

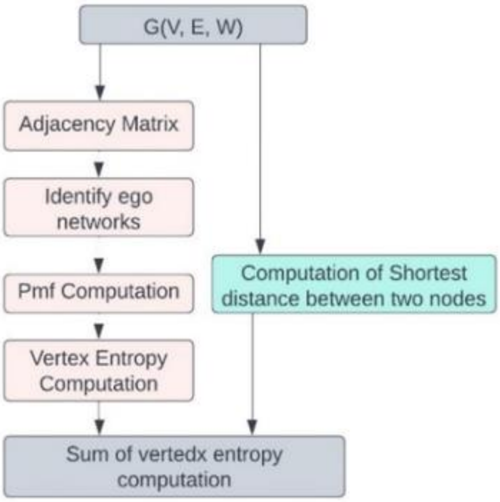

Fig. III. Work flow of algorithm

- The technique calculates the ego networks for a given graph G (V, E, W) with n nodes.
- The approach calculates the probability mass function (pmf) for each network edge in the second phase.
- The vertex entropy of each vertex in the network is computed by the method in the third phase since it determines the centrality of each node.
- The approach normalises the outcome based on the shortest distance between the node pairs. When the SVE score increases, the likelihood of a connection between two nodes increasing.

VIII. DATA SETS AND EVALUATION METRICES

- A summary of the three real-world data sets used to evaluate the algorithm's performance is provided in this section. These datasets come from a variety of networks and disciplines. Two of the three datasets concern with unweighted networks, whereas the third concerns weighted networks. Table 1 provides the statistics of the used datasets.

Table 1: Dataset

Name of Data Set	No of Nodes	Data Set Type	Network Type
Power grid	4941	Commercial	Unweighted
Email communication network	1133	Commercial	Unweighted
Netscience	379	Co-authorship	Unweighted

- *Evaluation Metrices*: The performance of metrices is outlined and used to assess our models in this section.

1. AUC*:* This can be seen as the likelihood that a randomly chosen test graph edge would receive a higher score than a randomly picked test graph connection that does not exist. As a result, the scores of the connection which are absent and the score of the links that does not exist are constantly compared.
2. Precision: Precision is the proportion of TP to TP plus FP added together.

IX. RESULTS

This section provides a comparative study of the testing done to determine the effectiveness of the SVE algorithm. As the SVE algorithm falls within the category of similarity-based approaches, the similarity-based methods are taken for comparison. The comparison of the SVE algorithm's output to the other baseline algorithms is shown in the table below.

TABLE 2: AUC Comparison results

Data Set	Power Grid	Email	Net Science
CN	.626	.855	.626
JC	.603	.861	.968
AA	.624	.859	.969
RA	.625	.858	.981
KZ	**.965**	.881	.982
SVE	.571	**.885**	**.988**

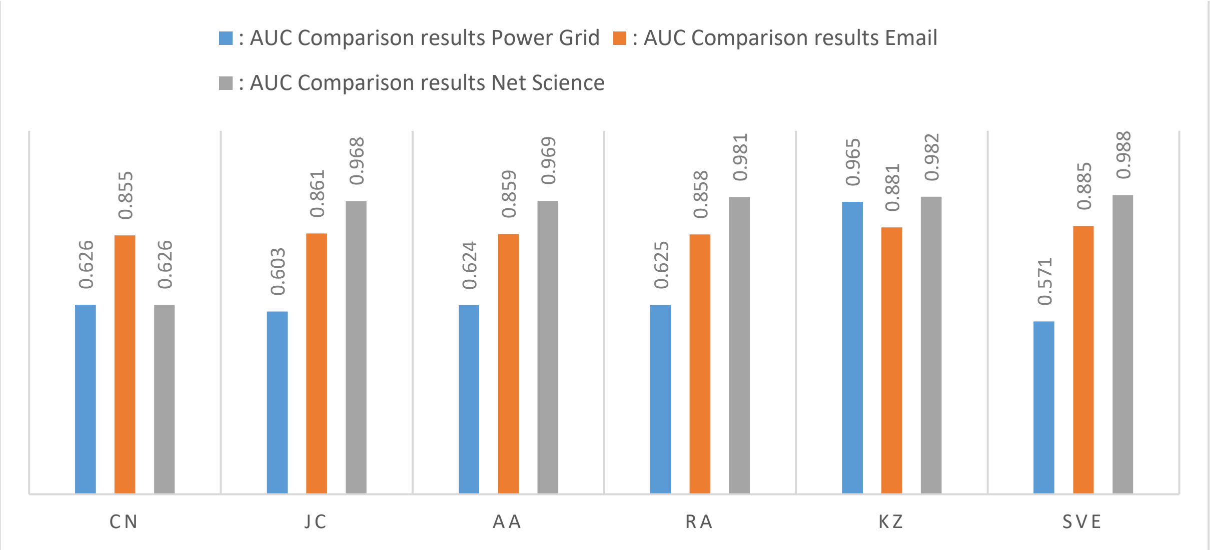

Fig. IV. Performance analysis based on AUC

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The datasets and link prediction techniques used in the experiments are shown in the first row and first column of each table in the results section. The comparative findings for three unweighted networks are shown in Table 2. The innovative approach outperforms the six baseline link prediction algorithms, as shown in Table 2. The SVE approach provides considerably superior AUC values, especially for Net Science. The SVE algorithm returns an AUC value of.988, which is nearly equivalent to 1, for Net Science. The proposed approach here clearly outperforms the second-best baseline algorithms in terms of performance.

TABLE 3: Precision Comparison results

Data Set	Power Grid	Email	Net Science
CN	.051	.139	.398
JC	.0006	.069	.175
AA	.030	.151	.609
RA	.030	.138	.634
KZ	.058	.131	.642
SVE	**.146**	**.341**	**.775**

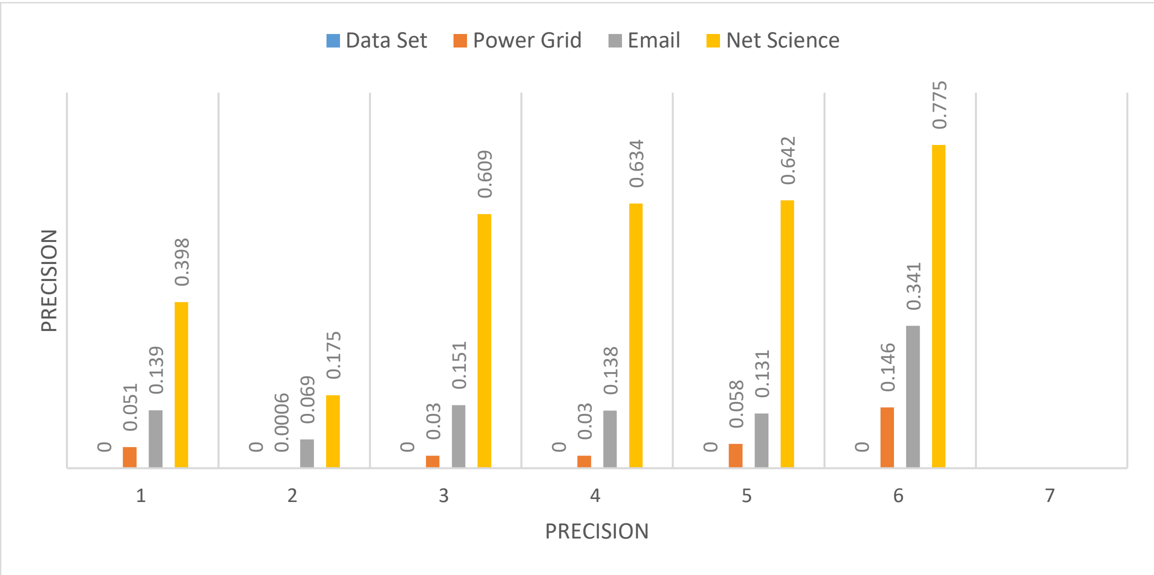

Fig. V. Performance analysis based on Precision

The first row and first column of each table in the results section show the datasets and link prediction techniques applied in the experiments. Table 2 displays the comparison findings for three unweighted networks using AUC. According to Table 2, the novel algorithm performs better than the six baseline link prediction algorithms. The SVE method produces noticeably higher AUC values, particularly for Net Science. The SVE algorithm returns an AUC value for Net Science of.988, which is nearly equivalent to 1. Obviously, the suggested method in this case performs better than the second-best baseline algorithms.

X. CONCLUSION AND FUTURE SCOPE

Calculating the vertex entropy and the ego network are two key components of the innovative method. The suggested technique accurately predicts the linkages in both weighted and unweighted networks. Using 3 real-world datasets, the SVE algorithm's performance is assessed. Also, the SVE algorithm is contrasted with 5 benchmark methods. Following the review of the AUC metric's findings in unweighted networks, the paper concluded that the recommended strategies work better when the dataset is dense. Nevertheless, if the network density is low, the performance of the algorithms begins to suffer. All networks produced good results therefore, this technique can also be applied to recommender systems, transportation network management systems, and e-commerce.

DECLARATION

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Authors Contributions	All authors have equal participation in this article.

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