A Nested Structure of Anomalies in Academic Publication Citations

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Abstract: The article presents a novel approach to detecting nested anomalies in citation networks. These anomalies, as irregularities within citation patterns, significantly threaten the reliability of academic research. Traditional methods for anomaly detection often study the entire citation graph, missing abnormalities within specific subfields or research clusters. Unlike these methods, our approach delves deeper by examining articles within the citation network at different nested scales. Such an approach allows anomalies that might be missed to be uncovered by focusing on a single level, revealing hidden patterns across various granularities, detecting a broader spectrum of nested irregularities, and offering a more nuanced understanding of how citation patterns deviate from the expected. The presented approach supports identifying potential issues, such as citation manipulation, and uncovering emerging trends within the network. The delivered numerical experiments also demonstrate the method's ability to estimate the consistency of the dataset structure.

1 INTRODUCTION

The research on anomalies in citation networks, a complex and pressing issue, is of utmost importance for the integrity and reliability of scholarly communication. Understanding these incongruities involves identifying multiple irregularities or unexpected outliers within the larger citation patterns. Investigating citation patterns at multiple levels can uncover critical insights, including identifying improper citations, potentially fraudulent activities, and emerging knowledge-sharing trends. Our approach aims to recognize potential issues, such as citation manipulation, and uncover emerging trends within the citation realm. The need for a more nuanced understanding of how citation patterns deviate from the expected is crucial for ensuring the integrity and reliability of scholarly communication and enhancing the accuracy of citation-based metrics and analyses.

The anomaly papers may manifest at multiple levels of the citation network hierarchy, indicating deviations or inconsistencies in citation patterns snuggled within broader citation relationships. Certain articles may exhibit abnormal citation behavior, such as a disproportionate number of citations from articles located in other clusters of papers. These irregularities may indicate citation manipulation, biased referencing, or emerging research trends within specific subfields. For instance, a paper may contain citations to obscure or irrelevant sources, self-citations intended to artificially inflate the author's citation count, or citations to predatory journals or discredited research.

While a paper may conform to expected citation norms, specific citations within the paper may stand out as inconsistent. Unethical citation practices are not just a minor inconvenience but a serious threat to the core principles of academic discourse – precision, impartiality, and scientific credibility. Researchers commonly acknowledge the uneven value of citations and attempt to differentiate them by type and importance (e.g., weighting), but this approach remains limited. Prabha's work (Prabha, 1983) underscores the gravity of the issue, revealing that over two-thirds of references in a paper might be needless. This statistic highlights the prevalence of dubious citations that undermine the integrity of the academic record.

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Scholarly citation practices are not immune to author bias, which takes various forms. Excessive self-citation, for example, occurs when authors cite their work excessively, potentially to bolster their publication count or perceived impact. Coercive citation involves reviewers or editors pressuring authors to cite specific references, sometimes including their own or those from journals.

Citation networks can exhibit phenomena like citation rings, where groups of researchers reciprocally inflate each other's citation counts, and ghost citations, fabricated references to strengthen arguments or create the illusion of broader support. Data-related issues, such as inaccurate reference formatting or ambiguity in author names, further complicate citation tracking. External influences, like the bias towards citing studies from prestigious journals or those funded by entities, also skew citation practices. Moreover, erratic citation patterns may emerge as scholars establish foundational works and methodologies in emerging research fields.

As widely acknowledged, citation analysis is focused on identifying various anomalies. This attention stems from the concern raised in the introduction that these anomalies may originate from inaccurate references in a specific context. The effectiveness of anomaly detection hinges on selecting the most appropriate algorithm for the specific data type and desired data-centric outcome.

Most studies in the mentioned field (see, e.g., (Liu 2022), (Liu, 2024)) concentrate on anomaly citation recognition, examining a citation graph in its entirety and losing the graph granularity. An anomaly paper in a citation network is one whose citation patterns deviate significantly from the norm for its field and topic. These deviations can indicate various issues, potentially impacting the integrity of the academic record. Such an anomaly is associated with the paper's position within the citation network. Unexpected co-citation patterns can signal anomalies, such as a highly cited paper only co-cited with irrelevant works.

The community structure is also important to consider, considering whether the paper belongs to a cluster of highly interconnected papers that exhibit unusual citation behavior. So, anomalies can exhibit a spectrum of deviations from the norm, indicating that their departure from typical patterns can vary in severity across different instances, creating a nested anomaly structure.

Unlike traditional methods, this paper presents a multi-level analysis for more comprehensive detection, examining articles at various granularities to uncover overlooked irregularities. The findings of this research can be applied to various fields, including citation analysis, software engineering, and scholarly communication, to detect irregularities, uncover emerging trends, and enhance the accuracy of citation-based metrics and analyses, thereby improving the quality and trustworthiness of academic research evaluation.

Aiming to recognize anomaly papers on nested citation levels, we base our research on the method proposed in (Tang, 2022). It is an innovative approach to harnessing spectral information within Graph Neural Networks (*GNNs*) to detect anomalies. It proposes a new network architecture called a Beta Wavelet Graph Neural Network (*BWGNN*).

The proposed method involves a detailed examination of articles' location in a network, starting from their broad structural attributes and narrowing down to finer connection elements to identify anomalies in the citation nested patterns.

Aiming to prepare the initiating anomaly sets in data clusters, a citation graph is embedded using the Node2Vec method (Grover, 2016) and clustered in a linear space. Subsequently, the outer shell of the clusters—those points most distant from the cluster centers—is identified as the initial set of anomalies. We employ the BWGNN network trained on a dataset with elements assigned as anomalies or normal elements to better understand the identified anomalies. After categorizing the data points, the network identifies anomalies and their connections within the network. These anomalies are then removed, resulting in a cleaner dataset. The process is then repeated using this reduced graph to refine the detection and analysis of anomalies at further deeper levels.

2 MATHEMATICAL FRAMEWORKS

Subsections 2.1 and 2.2 establish the background for *BWGNN* to be employed throughout this study.

2.1 Signal on Graphs

An attributed graph, $G = \{V, E\}$, is characterized in this study by a collection of nodes V and unweighted edges E connecting the nodes. The degree matrix D is a diagonal matrix where D_{ii} denotes the degree, or number of connections, of vertex i. The adjacency matrix A is a square matrix where A_{ij} signifies the presence (with a 1) or absence (with a 0) of an edge between vertices i and j. Let $L=D-A$ be the regular

Laplacian (not that the normalized one also can be used) matrix with eigenvalues arranged in ascending order, $0 = \lambda_1 \leq \cdots \leq \lambda_N$, and a corresponding orthonormal basis of eigenvectors $U = (u_1, u_2, \dots, u_N)$.

Except for the two endpoints λ_1 and λ_N the remaining eigenvalues can be partitioned into low frequencies $\{\lambda_1, \lambda_2, \cdots, \lambda_k\}$ and high frequencies $\{\lambda_{k+1}, \lambda_{k+2}, \dots, \lambda_N\}$ using an arbitrary threshold λ_k. The paper (Tang, 2022) brings attention to the "right-shift" phenomenon concept. Anomalies disturb a graph's spectral energy distribution, causing it to shift towards higher frequencies. So, regular graphs display a specific energy pattern, but anomalies disrupt this pattern by focusing more energy on high-frequency elements.

This concept can be clarified by considering the known case of the Fourier transform on graphs. Just like a regular Fourier transform breaks down a complex signal into its basic frequencies, the graph Fourier transform acts as a similar tool for network data. It decomposes the data into fundamental components unique to the network's structure.

Here, the spectral energy distribution of a signal $x = (x_1, x_2, \cdots, x_N)^T \in R^N$ on a graph is given by the signal's frequency components obtained by the named transform

$$\hat{x} = (\hat{x}_1, \hat{x}_2, \cdots, \hat{x}_N)^T = U^T x .$$

Let us introduce

$$p(\lambda_k) = \frac{\hat{x}_k^2}{\sum_{t=1}^{N} \hat{x}_t^2}$$

as the spectral energy distribution at λ_k $(1 \leq k \leq N)$. The famous coefficient of variation can be interpreted as the level of anomalies present in the distribution. An increasing proportion of anomalies corresponds to a more significant coefficient of variation in the energy distribution. If the distance between anomalies and the mean vector expands, the indicator also rises, designating a greater degree of anomalies. To quantify the changes in the spectral energy distribution relative to the degree of anomalies, a metric called the Energy Ratio is introduced as follows:

$$\eta_k(x, L) = \frac{\sum_{t=1}^{k} \hat{x}_t^2}{\sum_{t=1}^{N} \hat{x}_t^2} , (1 \leq k \leq N - 1).$$

Generally, as the coefficient of variation increases, the expected value of the inverse of the low-frequency energy ratio also increases. This means that a greater number of outliers or anomalies in the dataset results in a higher average of the inverse low-frequency energy ratio. Therefore, a greater degree of anomaly results in the spectral energy distribution showing reduced concentration on the low-frequency eigenvalues. A spectral energy ratio can be used to detect anomalies in a graph. However, this method is sufficiently complex and slow for large graphs. A simpler and faster method has been proposed, focusing on the spectral domain.

To accomplish this, a piecewise linear function is introduced within the interval from zero to λ_{N-1}. Between two successive eigenvalues $[\lambda_k, \lambda_{k+1}]$ this function equals to $\eta_k(x, L)$. The residual area between this simplified curve and a line representing constant energy (*g(t) = 1*) is termed the high-frequency area (S_{high}). It can be calculated through elementary manipulations without the necessity for eigendecomposition:

$$S_{high}(x) = \frac{x^T L x}{x^T x}.$$

This equation demonstrates the close relationship between a signal's energy distribution in the spectral domain and the smoothness in the spatial domain. Consequently, when the signal x demonstrates similar values between connected nodes, resulting in a smaller $x^T L x$ suggests a lower degree of irregularity.

2.2 Beta Wavelet Graph Network

As indicated in (Tang, 2022), many existing Graph Neural Networks (*GNNs*) face challenges from using low-pass filters and prioritizing information from lower frequencies, potentially leading to oversight of high-frequency anomalies of interest. While adaptive filters allow them to adjust their focus, they may still need more specificity in targeting the frequency band where anomalies reside (band-pass) or accurately pinpointing the location of these anomalies within the graph (spectral-localized). This issue arises because, even in anomalies, a substantial portion of the graph's energy remains concentrated on lower frequencies. Consequently, these adaptive *GNNs* may exhibit behavior akin to low-pass filters, potentially missing critical high-frequency anomalies.

To better handle anomalies, a new graph neural network architecture is proposed based on Hammond's graph wavelet theory (Hammond, 2011), which is well-known for its band-pass nature. This theory represents a significant advancement in signal processing and analysis, as it extends the capabilities of wavelets to graphs. Researchers can analyze signals within intricate graph structures, unlike traditional wavelets limited to Euclidean spaces. It provides them with a robust toolkit for conducting localized analysis on graphs, like how wavelets facilitate the examination of signals in time or frequency domains.

Generally, this graph wavelet transform is created on a "mother" wavelet ψ and utilizes a set of wavelets as bases, denoted as $W = (W_{\psi_1}, W_{\psi_2}, \cdots)$. In formal terms, the application of W_{ψ_i} to a graph signal $x \in R^N$ can be expressed as:

$$W_{\psi_i}(x) = U g_i(\Lambda) U^T x.$$

To avoid computing the eigen decomposition of the graph Laplacian, the kernel function g_i is chosen commonly as a polynomial function represented as

$$U g_i(L) U^T = g_i(L)$$

The presented research selects a slightly modified beta distribution density as the graph kernel function:

$$\beta_{p,q}(w) = \begin{cases} \frac{1}{B(p+1,q+1)} w^p (1-w)^q, & if\ w \in [0,1] \\ 0 & otherwise \end{cases}$$

where $p, q \in R^+$ and B is the standard Beta function, also called the Euler integral of the first kind. Aiming to cover all eigenvalues $\lambda \in [0,2]$ of the normalized graph Laplacian L a modified kernel

$$\beta^*_{(p,q)(w)} = \frac{1}{2}\beta_{(p,q)}\left(\frac{w}{2}\right)$$

$\beta^*_{p,q}$ is a polynomial for $p, q \in \mathbb{N}^+$. Thus,

$$W_{(p,q)} = U\beta^*_{(p,q)}(\Lambda)U^T = \frac{(L/2)^p (I - L/2)^q}{2B(p+1, q+1)}$$

Let us choose a constant $p + q = C$ to generate a set of $C+1$ the Beta wavelet transforms W with the same order:

$$W = (W_{0,C}, W_{1,C-1}, \ldots, W_{C,0}).$$

Here is a low-pass filter $W_{0,C}$, However, all the other functions provide band-pass filters of different scales. Based on the introduced beta graph wavelet, *BWGNN* is proposed for anomaly detection.

$$Z_i = (W_{i,C-1}(MLP(X)), H = AGG(Z_0, Z_1, \ldots, Z_C).$$

MLP(·) represents a multi-layer perceptron, while *AGG(·)* is a basic aggregation function like summation or concatenation. Following aggregation, the resultant representation H is forwarded to another *MLP* employing the Sigmoid function to determine the abnormal probability.

2.3 Node2Vec Graph Embedding

Analogous to word embedding, graph embedding methodologies are designed to distill the fundamental attributes of nodes and edges within a graph into continuous vectors of diminished dimensions. In a manner akin to word embeddings, which elucidate the semantic nuances and interrelationships among words in textual contexts, graph embeddings elucidate the structural layout and interconnections intrinsic to a graph.

The famous *Node2Vec* approach (Grover, 2016) constitutes a particular algorithm employed for graph embedding, which addresses converting a graph into numerical representations for each node. Termed embeddings, these numerical representations encapsulate the relationships among nodes within the graph. Analogous to word embedding, where words with analogous meanings possess similar embeddings, *Node2Vec* attempts to generate embeddings wherein closely interconnected nodes within the graph exhibit analogous numerical representations.

Node2Vec uses random walks on graphs, with a bias, during this exploration process. This bias allows it to balance two important aspects of a node's neighborhood: Homophily and Structural Equivalence. Two settings, namely "return" and "inout", regulate the algorithm's exploration behavior by covering the network. These settings influence the direction of the random walk, dictating its next steps.

- Local Exploration: "Return(p)" - This setting governs the likelihood of the walk revisiting recently traversed nodes. A higher "return" value results in the walk staying near its starting point, emphasizing the exploration of the local neighborhood and capturing the network's structural characteristics.
- Global Exploration: "Inout(q)" - This setting determines whether the walk explores outward to new regions or inward towards previously visited nodes. A higher "inout" value encourages outward exploration, facilitating the discovery of diverse network regions.

Node2Vec balances exploring novel graph areas and exploiting information from neighboring nodes by adjusting settings, particularly using probabilities *1/p* and *1/q*.

After generating random walks, *Node2Vec* considers each walk ostensibly a sentence in natural language and encodes the nodes using Word2Vec word embeddings. *Node2Vec* operates with the Skip-gram approach, where the embedding captures the structural similarities between nodes, effectively translating their proximity or connectivity within the network. The Skip-gram model is trained on a large text corpus. For each word (target), the approach considers a window of surrounding words (context) and aims to predict these context words based solely on the internal representation of the target word.

3 NESTED ANOMALIES' STRUCTURE APPROACH

The proposed procedure seems to unfold as follows:
***Algorithm 1*.**
Pseudocode of the procedure:
Input parameters:

- *GraphG* -A citations graph.
- Node2Vec procedure:
  - ✓ *p* and *q* – "return" and "inout" parameter values.
  - ✓ *Nwalk*- The number of random walks.
  - ✓ *Lwalk*-a length of a random walk.
  - ✓ *d*- a dimension of the Word2Vec embedding.
- *H*-a number of levels in the hierarchy.
- *Cl*- a clustering algorithm with K_{Cl}- a number of the clusters in *GraphG*.
- *Fr* - a core fraction in clusters.
- *C*-a constant to generate a set of *C+1* the Beta wavelet transforms

Procedure:

a. Load the dataset *GraphG*.
b. Initialize the set of anomaly nodes $V_a = \emptyset$.
c. For *iter = 1: H* do:
   1. Create a temporal dataset G_{iter} by omitting all anomaly nodes from V_a together with the connections between V_a and $GraphG \backslash V_a$.
   2. Create an embedding of G_{iter}:
      $W(G_{iter}) = Node2Vec(G_{iter}, Nwalk, p, q, d)$.
   3. Cluster $W(G_{iter})$ using *Cl* into K_{Cl} clusters.
      a. Calculate distances from each point to its cluster centroid.
      b. In each cluster, select a fraction *Fr* of the points closest to the centroid as the cluster core while designating the remaining points as anomalies.
      c. Update V_a as a union of all cluster anomalies.
      d. Update V_n as a union of all cluster cores.
      e. Train $BWGNN(C)$ on V_a, V_n
      f. Assign each node in G_{iter} recognized as an anomaly to set V_a.

d. Summarize the results.

4 NUMERICAL STUDY

4.1 CORA Dataset

The CORA dataset is famous for machine learning and natural language processing researchers, especially those interested in citation networks. It is a collection of computer science research papers. Each paper is represented as a bag of words by terms appearing in the paper. The dataset also includes information on how these papers cite each other, forming a network of citations. So, CORA has the following features:

- 2,708 Scientific Papers (the nodes of the network)
- 5,429 Citation Links
- A binary bag of words Vector for Each Paper based on a dictionary of 1,433 unique terms.
- 7 Paper Categories: The papers are neatly classified into 7 different areas as presented in Table 1.

Table 1: Research Areas Presented in the CORA Dataset.

	Field	Amount
1.	Neural Networks	818
2.	Probabilistic Methods	426
3.	Genetic Algorithms	418
4.	Theory	351
5.	Case-Based	298
6.	Reinforcement Learning	217
7.	Rule Learning	180

Figure 1 partially visualizes the CORA dataset resting upon 2000 nodes. Different categories are colored another way. The experiments are conducted using a specified set of parameters.

- *p = q = 1.*
- *Nwalk = 200.*
- *Lwalk = 50.*
- *d = 64.*
- *H =10.*
- *Cl*- the *PAM* algorithm (see, e.g., (Kaufman, 1990)) with the *K*-means++ initialization and $K_{Cl} = 7$.
- *Fr = 0.7, 0.8, 0.9.*
- *C= 64*

It is important to note that while the number of clusters used in the algorithm matches the number of categories, the resulting partition does not correspond to the original categorization. The Cramér's V correlation coefficient between two partitions is 0.048, indicating an absence of significant correlation. This discrepancy likely arises due to differences in how papers are assigned. The applied embedding method inherently relies on the citation base partition. The obtained results are presented in Tables 2-4.

Table 2: Distribution of anomaly papers during the sequential iterations and inherent categories for cora for FR=0.7.

Iteration\ cluster	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Sum**
1	26	2	17	11	11	0	10	77
2	1	16	16	0	15	10	9	67
3	5	4	7	0	9	25	9	59
4	21	17	12	7	25	4	1	87
5	16	8	1	5	1	11	6	48
6	1	7	14	17	2	38	13	92
7	3	7	0	7	6	13	4	40
8	3	15	0	1	7	14	8	48
9	6	13	0	8	2	15	8	52
10	21	9	7	7	6	33	0	83
Sum	103	98	74	63	84	163	68	

Table 3: Distribution of anomaly papers during the sequential iterations and inherent categories for cora for FR=0.8.

Iteration\ cluster	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Sum**
1	14	7	10	22	24	17	0	94
2	6	7	6	0	8	6	8	41
3	3	3	15	2	12	1	0	36
4	18	9	4	1	9	0	11	52
5	2	7	8	8	11	0	3	39
6	8	10	0	11	11	1	7	48
7	11	17	6	0	0	11	23	68
8	3	10	12	3	2	1	2	33
9	13	8	11	1	6	0	1	40
10	2	8	15	1	7	6	6	45
Sum	80	86	87	49	90	43	61	

Table 4: Distribution of anomaly papers during the sequential iterations and inherent categories for cora for FR=0.9.

Iteration\ cluster	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Sum**
1	14	13	0	4	10	11	1	53
2	4	9	9	1	3	3	5	34
3	4	7	3	9	6	4	0	33
4	4	3	5	5	3	13	1	34
5	2	3	2	2	2	18	0	29
6	1	0	1	0	0	13	0	15
7	3	0	5	0	4	11	0	23
8	2	8	6	1	10	8	3	38
9	9	2	3	8	2	0	6	30
10	0	2	3	0	0	0	0	5
Sum	43	47	37	30	40	81	16	

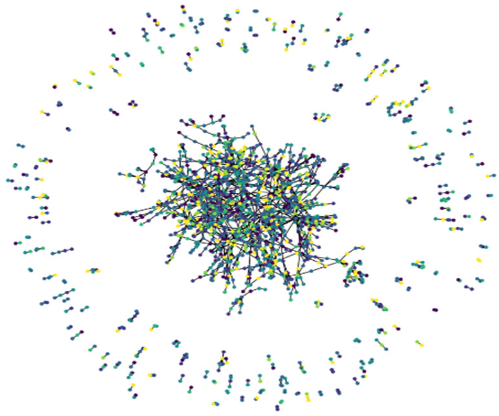

Figure 1: Partial visualization of the CORA dataset.

It appears interesting to consider the behavior of the number of nested anomalies during iterations. The following Figure 2 demonstrates an example of such a performance for $Fr=0.9$ through 30 sequential iterations.

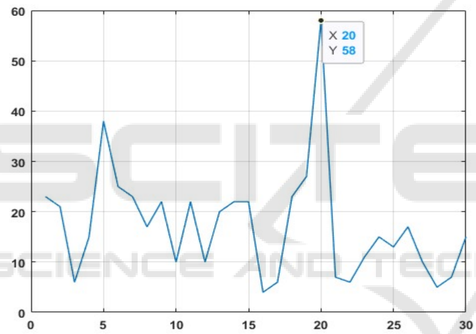

Figure 2: The averaged number of anomalies calculated for CORA data with $Fr=0.9$ through 30 sequential iterations.

This observation underscores the robustness and stability of the CORA dataset's structure. As the number of iterations increases, the characteristic behavior consistently demonstrates a natural tendency to decrease, indicating a reliable and well-defined framework within the dataset.

4.2 PubMed-Diabetes Dataset

The "PubMed-Diabetes Dataset" is a meticulously curated compilation of scientific articles delving into diabetes research sourced from the extensive biomedical literature on PubMed. Managed by the National Center for Biotechnology Information (NCBI) and the U.S. National Library of Medicine, PubMed is a central hub for accessing scientific advancements across the life sciences. This database encompasses many publications, including research papers, reviews, and scholarly articles spanning various biomedical disciplines. Leveraging this extensive repository, the PubMed-Diabetes dataset focuses on articles investigating different aspects of diabetes, offering valuable insights into this complex condition.

To delve into the thematic connections among articles in diabetes research, we adopted a subset analysis approach. Specifically, we randomly extracted 3000 nodes from the PubMed-Diabetes dataset, constituting roughly 10% of the entire dataset. This sample size is deemed statistically significant for conducting network analysis. Remarkably, within this subset, we identified 1995 edges, representing approximately 90% of the total, indicating links between the respective articles.

Exploring this subset of the PubMed-Diabetes dataset allows us to analyze thematic relationships and uncover potential knowledge gaps, like the CORA dataset analysis. The analysis provided for this sampled dataset with the exchange of K_{Cl} value to 3, which is the inherent number of the categories in the dataset, supplies the following result for $Fr=0.9$. (see, Table 5).

Figure 3 presents the average number of anomalies calculated for PubMed data with $Fr=0.9$ through 10 sequential iterations.

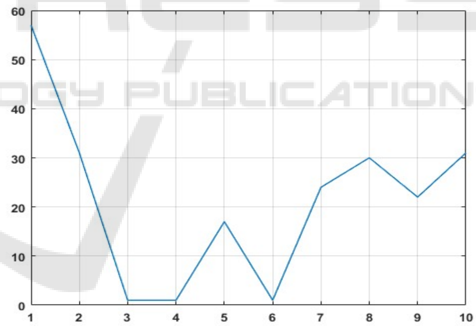

Figure 3: The average number of anomalies calculated for PubMed data with $Fr=0.9$ through 10 sequential iterations.

This curve exhibits more unstable behavior than the graph shown in Figure 2.

This instability could be attributed to the random sampling method used to construct this dataset. The inherent randomness in the sampling process likely introduced more significant variability, leading to the observed fluctuations in the curve. This suggests that the inborn data structure significantly affects the resulting stability.

Table 5: Distribution of anomaly papers during the sequential iterations and inherent categories for PubMed for *Fr=0.9*.

Iteration\cluster	1	2	3	Sum
1	54	1	2	57
2	29	1	1	31
3	1	0	0	1
4	0	0	1	1
5	17	0	0	17
6	0	0	1	1
7	24	0	0	24
8	0	30	0	30
9	0	21	1	22
10	20	1	10	31
Sum	145	54	16	

5 CONCLUSIONS

This paper introduces a novel multi-level analysis approach for detecting anomalies within citation networks. Unlike traditional methods that focus on a single level, this approach examines articles at various granularities, inspired by the work of (Tang, 2022), which leverages Beta Wavelet Graph Neural Networks (BWGNNs) to utilize spectral information for pinpointing anomalies. The proposed process begins with Node2Vec embedding and sequential clustering to identify initial anomalies. The Node2Vec approach is applied to embed the current graph into Euclidian space, making it possible to use clustering to reveal the initial anomalies set fed into *BWGNN* for further refinement. The detected outliers and their connections are removed, resulting in a cleaner dataset. This process is repeated, each iteration revealing at each step a level in a nested structure of anomalies within the citation network. This stable structure is essential for conducting accurate and meaningful analyses, ensuring reliable results, and genuinely reflecting the inherent relationships among the data items.

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