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Large Scale Network Structure Inference Algorithm Based on Probabilistic Graph Modeling

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Abstract: - Interactions between individuals or entities exhibit dynamic characteristics, often depicted through a series of network snapshots, capturing interactions within short timeframes. Central to analyzing these evolving networks is the task of change-point detection. This involves pinpointing moments when the overarching interaction pattern undergoes significant shifts and measuring the scale and nature of these changes.. Thus, they develop a strategy that consistently solves the network change-point detection issue and formalise it inside an online probabilistic learning framework. The proposed method is Equivariant Quantum Neural Networks (EQNN). This method combines a user-defined parameter that specifies a goal false-positive rate with a flexible hierarchical random graph model that uses the Bayesian hypothesis test. EQNN method is used to change-point detection and aiming to identify changes in the large scale structure of evolving networks. The proposed method shows better existing method like graph neural network (GNN), Convolution Neural Network (CNN) and Multilayer Perception Neural Network (MPNN). The proposed method has error value of 0.5% which is lower than that of GNN, CNN and MPNN whose error values are 0.9%, 1.3% and 1.7% respectively.

Keywords: Change-point detection, Hierarchical random graph model, Evolving networks, Generative models, Bayesian hypothesis test, Probabilistic learning, Real-world data.

I. INTRODUCTION

Networks serve as a fundamental framework for analyzing interactions among objects or individuals, aiding in the comprehension of large-scale interaction structures. Traditional methods often overlook the dynamic nature of these interactions, necessitating the detection of non-stationary structures within real networks [1, 2]. Understanding the evolution of such systems involves identifying changes in their large-scale structure over time, which can stem from periodic behaviors or external events in social networks. This topic pertains to network change-point identification, and an online probabilistic learning approach is suggested to tackle it. This approach entails inferring a structural "norm" across a sequence of graphs and detecting shifts in this norm, allowing for the characterization of the type and magnitude of changes [3, 4]. Unlike conventional anomaly detection techniques, which only look for deviations from a stationary norm, our approach divides a network's evolution into periods of relative structural stability so that each period can be analysed separately and theories about underlying processes can be developed.

a) Background

People's and things' interactions are frequently dynamic and can be seen as a series of networks, each of which shows a moment in time in which the interactions occurred. Change-point detection is a crucial task in the analysis of such dynamic networks, where the measure the extent and kind of the change that has occurred, as well as identify the points at which the large-scale pattern of interactions fundamentally alters [5, 6]. Here, a trustworthy solution to the network change-point detection issue is presented in the context of an online probabilistic learning framework for the first time. This approach aims to statistically ascertain whether, when, and precisely how a transition point has happened by combining a Bayesian hypothesis test with a generalised hierarchical random graph model. Using synthetic data with known change points of various sorts and magnitudes, the detect ability of our method and demonstrate its superior accuracy over numerous previously employed alternatives. This approach finds a series of change points that correlate to known external "shocks" to two high-resolution evolving social networks [7, 8].

b) Challenges

The dynamic and intricate structure of real-world interactions presents challenges for network change-point identification. Conventional methods may fail to take into account the non-stationary nature of networks, making it more difficult to accurately identify notable changes in interaction patterns over time. Distinguishing

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between genuine changes and random fluctuations poses a significant challenge, requiring robust statistical methods to differentiate signal from noise. Moreover, interpreting the nature and magnitude of detected changes necessitates models that provide meaningful insights into the network's large-scale structure [9, 10].

The diverse sources of change, including periodic behaviors and external events, further complicate the detection process, underscoring the need for adaptable and interpretable detection techniques capable of capturing a wide range of change types and sizes in evolving networks.

c) Literature Review

In literature, various research works were based on large scale network structure inference algorithm on techniques and aspects. Some of them were reviews were followed.

Shi et al. [11] have presented to "optimize" methods in various 6G wireless network domains by figuring out the fundamental aspect of the underlying optimization issue and looking at the specially created ML frameworks from an optimization standpoint. In particular, this section will cover the use of graph neural networks for structured optimisation, end-to-end learning for semantic optimisation, learning to branch and bound, deep reinforcement learning for stochastic optimisation, and algorithm unrolling to solve challenging large-scale optimisation problems resulting from numerous important wireless applications. Federated learning for distributed optimisation, which enables the use of machine learning in dispersed wireless networks involving several endpoints, will also be covered. By means of a comprehensive discourse, about the superior efficacy of machine learning (ML)-driven optimization algorithms vis-à-vis traditional procedures, and offer perceptive recommendations for the advancement of ML methodologies in 6G networks. In addition, talks about neural network design, theoretical tools of different ML techniques, implementation difficulties, obstacles, and future research goals were held to help with the practical usage of ML models in wireless applications.

Zheng et al. [12] have presented concentrate on assessing new hybrid deep learning models for traffic prediction. In order to achieve this, the first analyzed the models and classified them according to how they extracted features. They look at their architectural plans and building components. So the performance comparison research using ten models that selected from our taxonomy to represent various architectural decisions. To achieve this, recreated the chosen models and conducted a set of identical comparative tests using three popular real-world datasets gathered from extensive road networks.

Chiroma et al. [13] have presented Machine learning has replaced conventional modeling approaches for path loss modeling in wireless communication systems due to its robustness and performance. There have been surveys in the literature on path loss modelling in communication systems; however, the surveys that have previously been published do not include comprehensive evaluations of the new deep learning architectures, machine learning taxonomies linked to path loss, and feature engineering in path loss modelling. This study was unique in that it closes the existing gap by addressing the aforementioned issues by performing a survey on machine learning modelling for route loss in wireless communication systems. Deep learning architectures were combined and examined here to address route loss problems in communication networks. New taxonomy, nature-inspired meta-heuristic algorithms, and shallow route loss modelling techniques have all been developed.

Ding et al. [14] have presented a vast set of baselines for ODAI and the Dataset of Object deTection in Aerial Imagery. Collected from 11,268 aerial images, the proposed DOTA dataset consists of 1,793,658 object instances of 18 different types of oriented-bounding-box annotations. The developed baselines encompassing ten cutting-edge algorithms with more than 70 configurations based on this extensive and well-annotated dataset. Each model's accuracy and speed performances were assessed. Moreover, to provide a code library for ODAI and develop a website that compares different methods.

Morariu et al. [15] have presented a hybrid control system that uses Big Data and machine learning approaches to analyse real-time data streams in industrial systems of huge sizes. The system focuses on energy consumptions that are aggregated at different levels. For data collection and format conversion, the control architecture was dispersed at the shop floor's edge. For data aggregation, machine learning, and intelligent decision-making, it was then centrally located at the cloud computing platform. Based on pertinent metadata, the data was compiled into logical streams and then combined. A neural network was then trained to identify any potential deviations or abnormalities from the typical patterns of energy use at each layer.

Haoran Li et al. [16] have presented Introducing MLFS-CCDE, a revolutionary multi-objectives large-scale cooperative co-evolution technique for three-objective feature selection. First of all, a cooperative searching framework was intended to find the ideal feature subset quickly and effectively. Secondly, the framework lays

out three goals: the quantity of features, the accuracy of the categorization, and the overall information gained. These goals were meant to direct the development of feature combinations. Thirdly, dual indicator-based representations were developed for the convolution process of the framework to balance the convergence and diversity of the representative solution, while a cluster-based decomposition method was developed for the decomposition process to minimize computation. In order to verify the framework's applicability, a cardiology-based heart disease detection system based on the MLFS-CCDE framework was constructed.

Ya et al. [17] have presented two principal inputs. The original plan was to capture over-the-air ADS-B signals in an open, real-world setting using an automated data gathering and tagging system that did not require human participation. To produce a high-quality collection of ADS-B signals for radio signal recognition, data cleaning and sorting were applied. Secondly, the new dataset to do a thorough analysis of the performance of deep learning models and compare our results with a recognition benchmark utilizing both ML and DL techniques.

d) Research Gap and Motivation

Determining the precise constraints or deficiencies in the existing machine learning-based optimization techniques for 6G networks could yield important information for future research avenues. The necessity to handle the intricate optimization issues in 6G wireless networks which call for effective and efficient solutions is what motivates the research covered in this document [18]. The objective is to improve 6G wireless network performance, facilitate intelligent communication systems, and support a range of applications in fields such as precision medicine, smart agriculture, and smart industrial by utilizing machine learning techniques. This research fills a vacuum in the literature by conducting a thorough performance comparison investigation of these hybrid models using real-world datasets under identical settings. Accurate traffic prediction is becoming more and more crucial for ITSs to handle the growing issue of urban traffic congestion. It is necessary to estimate the effectiveness of the most recent hybrid deep learning models for traffic prediction given the growth of traffic prediction approaches from statistical models to ML models and, more recently, deep learning models [19, 20]. Current reviews on path loss modeling in wireless communication systems do not provide in-depth study of feature engineering in path loss modeling, ML taxonomies pertinent to path loss, or upcoming deep learning architectures. The investigation of ML -based path loss modeling is driven by an awareness of the shortcomings of conventional path loss models and the possibilities of machine learning approaches to overcome these shortcomings. Furthermore, there are now more opportunities to improve path loss prediction efficiency and accuracy because to the development of deep learning systems.

e) Contribution

- This paper proposed a large scale network structure inference algorithm based on probabilistic graph modeling.
- The proposed method equivariant quantum neural networks (EQNN).
- EQNN method is used to change-point detection and aiming to identify changes in the large scale structure of evolving networks.
- The proposed model is implemented in the MATLAB working platform and the evaluated performance is compared with existing methods.

f) Organization

The following is the remainder of the document: segment 2 explains the proposed methodology large scale network structure inference algorithm based on probabilistic graph modeling. segment 3 explains results and discussion. segment 4 explains conclusion.

II. PROPOSED METHODOLOGY

The proposed methodology our proposed algorithm for inferring large-scale network structures relies on probabilistic graph modeling [21]. The employ an innovative approach utilizing equivariant quantum neural networks for change-point detection, specifically aimed at identifying alterations within evolving networks. Initially, implement the distribution over networks framework to facilitate change-point detection. Subsequently, detect Change Points in networks methodology, which focuses on detecting alterations in network connections. This serves as the final step in our real-time network analysis. Subsequently, the detectability of change points is assessed under controlled conditions using synthetic data. Ultimately, parametric bootstrapping is employed to evaluate the false positive rate of our algorithm. The block diagram for large scale network structure proposed EQNN method is represented in Fig 1. Accordingly, detailed description of all step given as below,

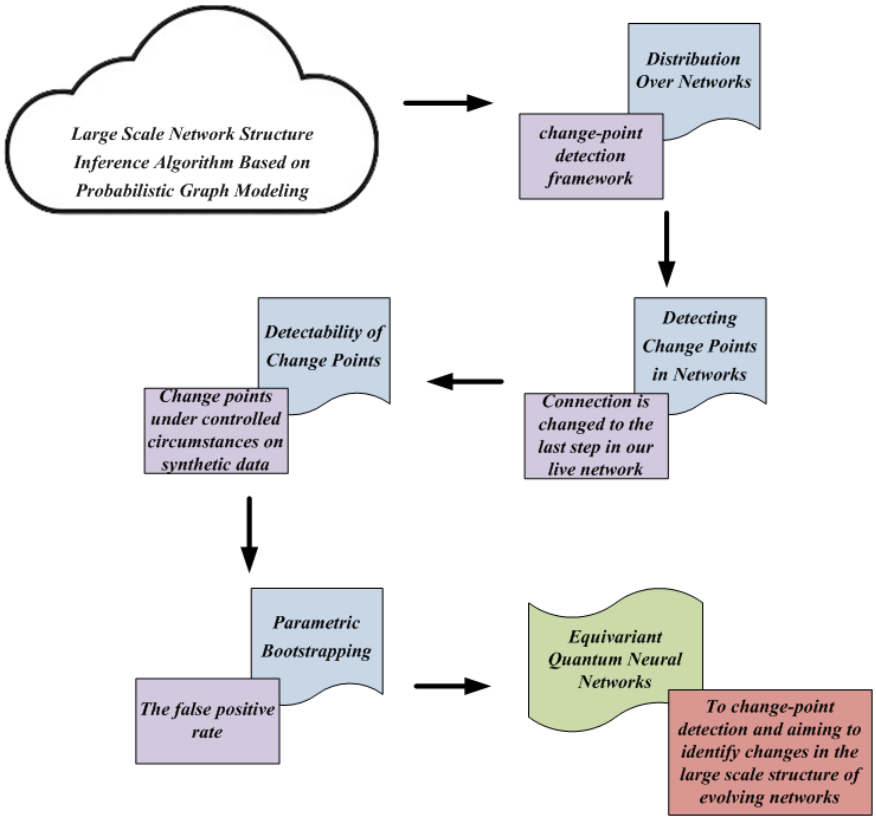

Fig 1: Block Diagram for large scale network structure proposed EQNN method

A. Probability Distribution Over Networks

The choice of a parametric distribution across networks is made in a probabilistic change-point detection approach. The GHRG model is shown here. This model generalizes the well-known HRG model and includes a number of features that make it appealing for change-point identification. First of all, the GHRG accurately and interpretably fits social, biological, and ecological networks and naturally captures patterns of both assortative and disassortative community structure. It also simulates the organisation of communities across all network dimensions. Secondly, our expansion lessens the necessity for the dendrogram to be a whole binary tree. This eliminates the HRG's inability to be identified and improves the model's interpretability when it comes to gauging the changes in a network's structure over a change point.. Third, so the employ a Bayesian model of connection probabilities to express how dubious about the generative model that underlies the network.

A network is modeled using GHRG $g=\{v,e\}$ made up of vertices v & borders $e\subseteq\{v\times v\}$. The model breaks down the n vertices into a number of nested groups, each of which has a dendrogram showing the relationships between them t. Vertices within g are the leaves of t, as well as the likelihood that two vertices V and U link in g is determined by a parameter P_R situated in the year of their lowest common ancestor t. Each tree node in the traditional HRG model is t has precisely 2 sub trees, and P_R provides the number of links among the left and right sub trees vertices. This means that different dendrogram and probability combinations result in the same distributions over networks, which makes the model non-identifiable. Prefer smaller trees and enable tree nodes to have any number of children to rule out this option in the GHRG. The GHRG defines a likelihood function and a distribution over networks given a tree and a collection of connection probabilities.

$$P\left(g\,|\,T,\{P_R\}\right)=\prod_R P_R^{e_R}\left(1-P_R\right)^{n_r-e_r} \quad (1)$$

Here e_R indicates the quantity of edges connecting vertices that share an ancestor, n_r and R indicates the entire count of edges that could possibly connect vertices that share an ancestor r,

$$n_R = \sum_{C_I < C_J \in c_R} |c_I \| c_J| \quad (2)$$

Here c_R, is the group of the eldest direct heirs of R and C_i refers to the group of network nodes that descend from the dendrogram node i.

Choosing the parameters for connection probability in one way $\{P_R\}$ would be to determine each of their values using the maximum probability method $\hat{P}_R = e_R / n_r$. This decision, however, leaves little room for doubt and will probably lead to a higher mistake rate in change-point identification. Take the scenario where there are exactly 0 connections $e_r = 0$, or, conversely, every relationship $e_R = n_R$, are noted for a certain branch R. In the event of maximal likelihood, the set $P_r = 0$ or 1. If a network that follows has or doesn't have even one edge with a common ancestor that is R, then $e_R > 0$ or $e_R > 1$, and the probability provided by equation 1 falls to 0, an ineffective result.

So the lessen this behavior by making the assumption that the P_R principles. Now, rather than placing P_R represent each pr as a distribution down to a point value, which measures our degree of uncertainty about its value and keeps its anticipated value from becoming 0 or 1. Use a hyper parameterized Beta distribution for convenience. $\alpha = \beta = 1$, This, over the parameters, corresponds to a uniform distribution P_R. This may analytically integrate out each of the P_R depending on parameters as the Binomial distribution and the Beta distribution are conjugate.

$$P(g \mid t, \alpha, \beta) = \prod_R \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \frac{\Gamma(e_R+\alpha)\Gamma(n_R - e_R + \beta)}{\Gamma(n_R+\alpha+\beta)} \quad (3)$$

B. Learning the Model

In order to fit the GHRG model to a network, all trees on N foliage and the matching probability sets of links $\{P_R\}$, which can achieve by applying methods from phylogenetic tree building and Bayesian posterior inference.

Tree structures need to be specifically searched, as they are not accessible to traditional convex optimization methods. It is expensive, nevertheless, to scan through every non-binary tree. Phylogenetic tree reconstruction presents a similar problem, which is usually handled by taking the majority "consensus" of a set of sampled binary trees. The collection of leaf bipartitions that are present in most tested binary trees is chosen by a consensus approach. Every group of divisions is a precise representation of a distinct non-binary tree containing those divisions. For example, if each sampled tree has a unique collection of bipartitions, then the consensus tree contains one internal node that is connected to each leaf node. Conversely, if all sampled trees are similar, they are likewise identical to the consensus tree. Consequently, calculate t in the GHRG by first sampling the posterior distribution of bipartitions using a Markov Chain Monte Carlo (MCMC) technique. Extract the non-binary majority consensus tree from this set of sampled bipartitions; however, this tree is not utilized to create a probabilistic model or determine link probabilities $\{P_R\}$ the remaining nodes in the tree.

Use this equation to update the posterior distribution over the parameter $\{P_R\}$ if a series of networks is observed g_t by making changes to the hyper parameters as

$$\tilde{\alpha}_R = \alpha + \sum_{\{g_T\}} e_r^{g_t} \quad \tilde{\beta}_r = \beta + \sum_{\{g_T\}} n_R - e_R^{g_T} \quad (4)$$

As a result, the posterior hyper parameters are calculated by adding the experimentally observed edge counts (the total number of connections that are present and absent) to the prior pseudo counts of edges. An implicit regularization is produced by this Bayesian method. As the quantity of observations n_R grows, the posterior distribution has more peaks, which indicates a reduction in the uncertainty surrounding the parameters. Parameters nearer the root of the GHRG model t symbolize more expansive constructions in g and control the

probability of additional edges. As a result, the estimation of these parameters is more certain, but the variance of the distribution of parameters far from the root, which indicate small-scale structures, is higher. This implicit regularization increases the resilience of the inferred norm to noise and inhibits over-fitting to small-scale structural alterations.

C. Detecting Change Points in Networks

Determining if and when the parameters of our present model of "normal" connection have changed is the last step in our live network change-point detection procedure. The posterior Bayes factor over a sliding window with a fixed length in order to achieve this W Check see whether there have been any modifications to the GHRG model that was installed over the window. The degree of abruptness required for a change to be observed depends on the size of the window. It is possible to detect more gradual changes with larger windows. If the factor surpasses a threshold set by a target false positive rate, a change is identified.

D. Posterior Bayes Factor

Use the posterior Bayes factor to decide whether or not to think a change has happened inside a specific window. The posterior Bayes factor, which is in line with our Bayesian framework and resembles a likelihood ratio test, is a ratio of the likelihood of the observed data under two different models: A model of the null hypothesis h_0, when nothing changes, as well as a different hypothesis model h_1, where a shift takes place at a specific moment T_C. On the other hand, rather of assessing the likelihoods under maximum likelihood parameters, to use the posterior marginal likelihood by weighting the average likelihood by the posterior distribution. This is computed for the GHRG by updating the previous hyper parameters (α, β) utilizing the posterior hyper parameters $(\hat{\alpha}, \hat{\beta})$.

So that only take into account change points that fall within a sliding window of W networks, with the final one existing at the "current" moment t . Assumed is the change point T_C takes place between a few pairs of images, which can show using a 0.5 offset. State that all networks inside the window for the no-change model were taken from a model with parameters $\varphi^{(0)}$. For the model of change allow $\varphi^{(0)}$ indicate the network model parameters up to T_C inside our window and $\varphi^{(1)}$ the network settings following T_C, but within the window nonetheless. Transposing the hypotheses about changes and no changes in terms of this shift in a parametric distribution over graphs at T_C,

$h_0 : \varphi^{(0)} = \varphi^{(0)}$ (No change) $h_1 : \varphi^{(0)} \neq \varphi^{(1)}$ (Change)

Using $\tilde{\varphi} = \{\tilde{\alpha}_R, \tilde{\beta}_R\}$ The posterior Bayes factor of the GHRG for a series of graphs is used to represent the set of posterior hyper parameters $\{g_{t-W+1}, ..., g_t\}$ is

$$\Lambda_{\hat{T}_C} = \log \frac{\prod_{T=t-W+1}^{\hat{T}_C - 0.5} P\left(g_T \middle| t_T, \tilde{\varphi}_{\hat{T}_C}^{(0)}\right) \prod_{T=\hat{T}_C+0.5}^{t} p\left(g_T \middle| t_t, \tilde{\varphi}_{t_c}^{(1)}\right)}{\prod_{T=t-W+1}^{t} P\left(g_T \middle| t_t, \tilde{\varphi}^{(\theta)}\right)} \quad (5)$$

Where $\tilde{\varphi}^{(0)}$ is the collection of posterior hyper parameters related to the no-change hypothesis, which states that there are no change points in the networks' window, while, $\tilde{\varphi}_{\hat{T}_C}^{(0)}$ and $\tilde{\varphi}_{\hat{T}_C}^{(1)}$ are the networks' hyper parameters up until and after the point $\hat{T}_c$ respectively.

And lastly, the moment the change happens T_C is an unknown quantity that needs to be estimated. Choose for conservatism, selecting $\hat{T}_C$ as the interval that optimizes our test statistic between two successive networks Λ through the window. Letting G_t for a specific time frame of W networks coming to an end at t be the greatest amount.

$$G_t = \max_{t-W+1<\hat{T}_C<t} \Lambda_{\hat{T}_C} \quad (6)$$

Next, state that the detection time T_D is the initial moment t when G_t surpasses a cutoff H

$$T_d = \min\{t : G_t > H\} \quad (7)$$

E. Parametric Bootstrapping

The threshold selection H, which G_t exceeds in order for a detection to happen, determines the false positive rate that the approach will produce, and the distribution of G_t based on the null model. The GHRG is a particularly helpful special example of the stochastic block model, of which recent studies on model comparison for statistical models of networks indicate that the null distribution may differ significantly from the x^2 distribution. The null distribution may be quantitatively estimated using Monte Carlo samples from a parametric bootstrap distribution provided by the GHRG for the no-change model, preventing an incorrectly designed test. By doing this, so that precisely estimates the null distribution as opposed to using a potentially inaccurate approximation.

To take a sample from the no-change GHRG model for every network and compute G_t from Eq. (5) in order to determine its distribution in the event of no change. The threshold h can then be selected using the sampled distribution in order that $P(G_t > H) = P_{FP}$ is the intended rate of false positives. In actuality, to accomplish this by computing a P-value for the test case by calculating the percentage of our null distribution's probability ratios that are greater than our test statistic G_t:

$$P - value = \frac{|\{G_t\} null > G_t|}{|\{G_t\} null|} \quad (8)$$

Therefore, in the event that discover a P - value when the no-change model is accurate, are wrong by no more than a threshold, and below that state a change is observed. P_{FP} , of the moment.

F. Detectability of Change Points

Prior to utilising our method on empirical data that has unknown structure and change points, thoroughly assess the detectability of various network change point kinds in controlled scenarios using artificial data that has been created using our GHRG model and has known structure and modifications.

The change-point categories listed below represent challenging but practical tests covering a wide range of large-scale alterations to network topology that have been seen empirically. In our numerical experiments, to select a network with $n = 30$ vertex count and an expected connection count that is both sparse and constant (marginal link probability of 0:2). Because it is more difficult to identify the norms in tiny networks due to the insufficient data, change points are more difficult to detect, making them a more challenging test case than bigger networks. In addition, To delineate 4 general categories of change points: formation (the splitting of a large community into two groups by adding edges); fragmentation (the losing of all edges in one group) and splitting (the merging of two communities, the time-reversal of splitting).

The structural index's definition $\mu = P_{out}/(P_{in} + P_{out})$ gives control over the transition between these different states with a single parameter. To select the merged state to be at the merge/split transition points $\mu = 0.5$, It results in a single community where each edge happens with an equal chance $P_{in} = P_{out}$. The network consists of two separate communities in the split state.

To employ the same two-community model for formation/fragmentation transition points, but let set the link probability inside one community and use μ to explain the connection between the P_{in} and P_{out} of the secondary community.

There are two distinct distributions (more than 100 runs) for every type of change: the approximate point of change $\hat{T}_C$ and the detection time T_D. To discover that the estimated change points are typically either somewhat early or accurate. The number of networks to need to observe following a change in order to determine the change point is measured by the time of detection, which is the point in the sliding window at which the change is detected. Data discover that while the merge and fragment changes are frequently estimated

early, their change spots are frequently discovered promptly. On the other hand, the estimation of the change points themselves is more accurate, but the split and formation changes are identified later.

G. Change points in real networks

Now use these methods1 to monitor two high-resolution emerging networks for changes: the MIT Reality Mining proximity network and the Enron email network. For each of these networks, a set of external "shocks" is available that may be used as targets for change-point identification. While representing distinct interaction kinds, both data sets are dynamic networks of social interactions between people. The measurement and the accuracy and recall of the performance in relation to the detection delay s between estimated
Change points $\{\widehat{T}_C\}$ and scheduled events $\{T_C\}$, i.e,

$$\text{Precision(s)} = \frac{1}{N_C}\sum_I \delta\left(\inf_J \left|\widehat{T}_C^{(I)} - T_C^{(J)}\right| \le S\right) \quad (9)$$

$$\text{Recall(s)} = \frac{1}{N_A}\sum_J \delta\left(\inf_I \left|\widehat{T}_C^{(I)} - T_C^{(J)}\right| \le S\right) \quad (10)$$

Here $\delta(x)$ specifies a function of delta that equals 1 if x is accurate and zero or else, and N_A and N_C are, correspondingly, the count of real events and “estimated change points”. The percentage of “estimated change points” that happen within a certain delay of a known occurrence is the precision. Likewise, recall is the percentage of known occurrences that take place within a certain amount of time after an “estimated change point”.

H. Social proximity network

The proximity data for 97 graduate students and faculty members at MIT was continually collected over a 35-week period using Bluetooth scans from their mobile phones. The constructed a series of weekly networks from the raw scan data, where each edge indicates that one of the 97 subjects is physically close to you at some point during the week. Sixteen recognized external events, such as public holidays, winter and spring breaks, exam periods, etc., are linked to the dataset.

The used a window size for every detection technique, including the GHRG and the 3 straightforward technique w = 4, identical to what was seen in the synthetic trials. Still, they also overlook most other incidents. The fact that only a total of two change points are identified by the mean degree and clustering coefficient, in particular, accounts for the excellent precision ratings. Moreover, there is less coherence across these techniques (except from the start of Sponsor week). As a result, these methods appear to be inconsistent and untrustworthy.

III. RESULT

In this paper proposed method based on EQNN approach for change-point detection and aiming to identify changes in the massive structure of dynamic networks. The proposed system is executed on MATLAB platform and contrasted to the a range of present approaches Photonic spiking neural networks (PSNN) The proposed method current value is optimal than the existing methods of graph neural network (GNN), Convolution Neural Network (CNN) and Multilayer Perception Neural Network (MPNN).

For each of the four strategies, the false positive and false negative error rates were investigated.. While all methods exhibited a false positive rate close to 0.05, consistent with the desired false alarm rate, there was significant disparity in false negative rates. The simpler methods consistently performed poorly, even in cases of substantial changes. Fig 2a illustrates the false negative bottom error rate of the merge method, with a maximum value of 0.73. The magnitude of change ranged from -0.4 $\Delta\mu$ at the start to 0.4 $\Delta\mu$ at the end. In Fig 2b, the split method exhibited a similar false negative rate, reaching a maximum value of 0.73. In Fig 3a, the analysis depicts false negative bottom error rates of the fragment method. The maximum false negative rate reaches 0.6, with a starting magnitude change value of 0.12 $\Delta\mu$ and ending at 0.9 $\Delta\mu$. Fig 3b presents a similar analysis of false negative bottom error rates, reaching a maximum value of 0.7 with magnitude changes starting at -0.1 $\Delta\mu$. On the other hand, our approach works well in all four tests, with the exception of the toughest instances, when tiny sample variations mask a large portion of the real change, such as when the change is extremely little.

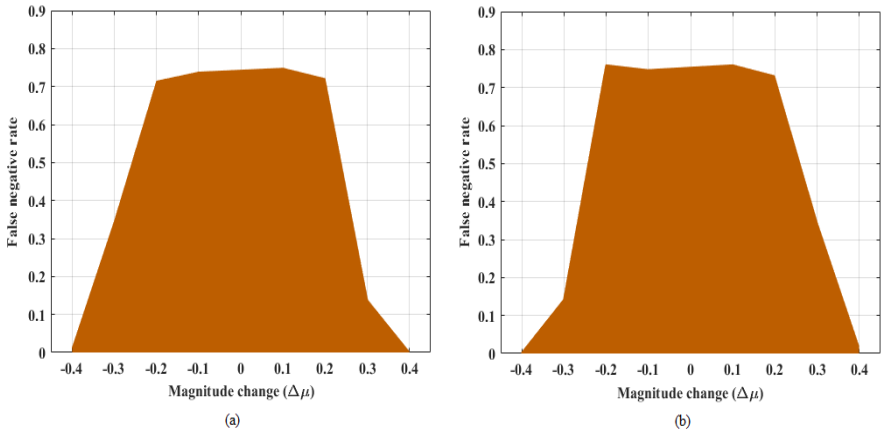

Fig 2: Analysis false negative bottom error rates (a) Merge (b) split

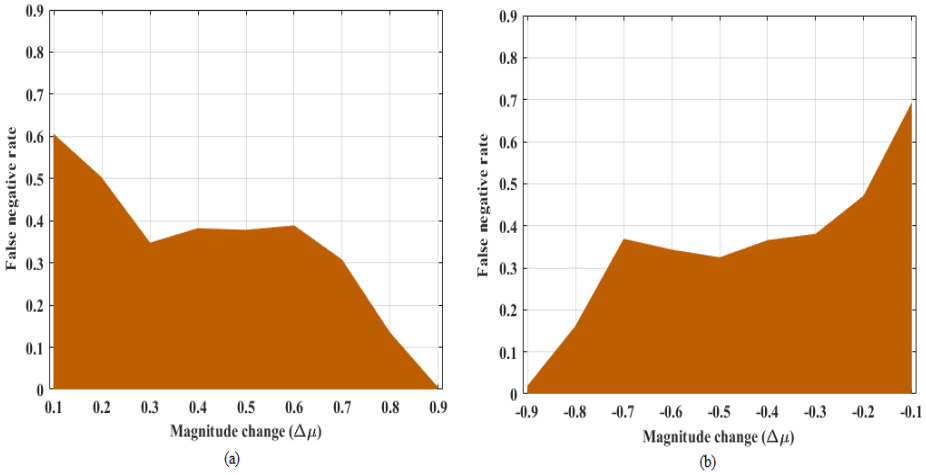

Fig 3: Analysis false negative bottom error rates (a) Fragment (b) Form

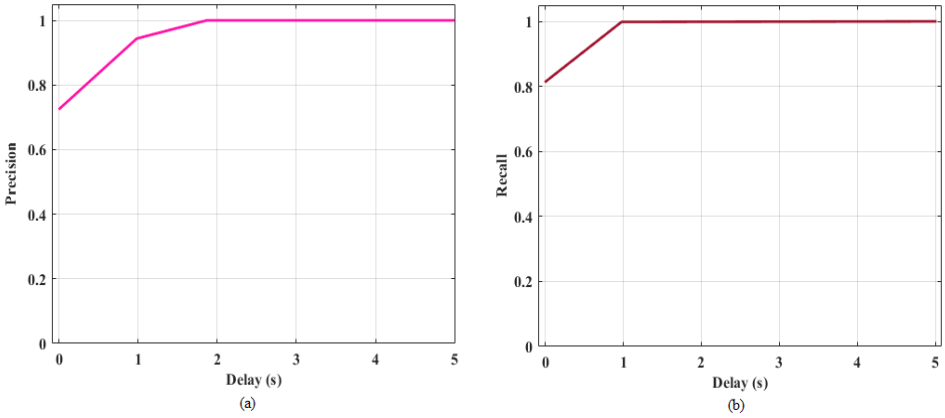

Fig 4: Analysis precision and recall (a) Precision (MIT) (b) Recall (MIT)

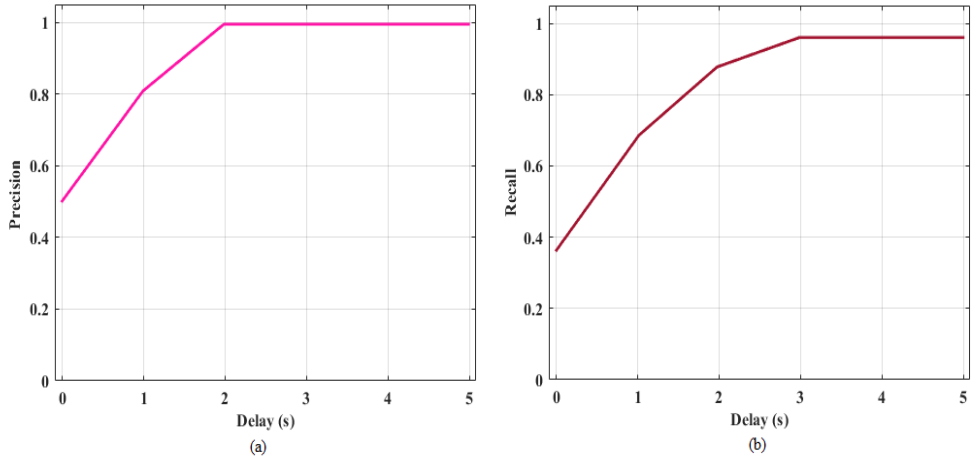

Fig 5: Analysis precision and recall (a) Precision (Enron) (b) Recall (Enron)

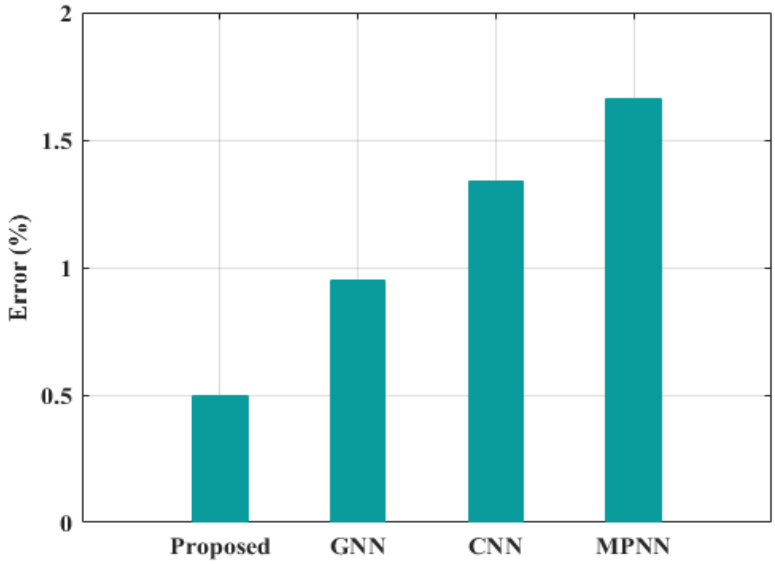

Fig. 6: Comparison of error value with proposed and existing methods

Observe that the clustering coefficient and mean degree exhibit slightly better precision compared to our approach, but our method significantly outperforms all baseline approaches in terms of recall .Subsequent analysis of the change-points identified by each of the basic techniques indicates that they are not very sensitive to known outside occurrences.. Fig 4a illustrates the Precision (MIT), starting from 0.72, reaching a maximum value of 1, with a maximum delay of 5 seconds. Fig 4b displays the Recall (MIT), which starts at 0.82, peaks at a maximum value of 1, with a maximum delay of 5 seconds. In Fig 5a, Precision (Enron) is depicted. The precision (Enron) initiates at 0.5 and reaches a maximum value of 1, with a delay of 5 seconds. Fig 5b illustrates the recall. The recall (Enron) begins at 0.39 and peaks at a maximum value of 0.98, with a delay of 5 seconds. Notably, these methods successfully identify several genuine change points, such as the winter break ,the start and the conclusion of the independent activities period. Fig 6 illustrates a comparison of error values. The proposed method exhibits a lower error rate of 0.5% compared to existing methods. Specifically, the maximum error rates are 1.7% for MPNN, 1.3% for CNN, and 0.9% for GNN.

A. Discussion

Comprehending the evolution of the network's structure over time and its potential future changes is a key objective when examining a series of time-evolving networks. A methodical solution to this issue is change-point identification, which breaks down a possibly non-stationary network sequence into smaller segments of unique but statistically stationary structural patterns. Here, have to introduce the 1st change-point detection technique using statistical hypothesis testing and generative network models for dynamic networks. The

proposed a statistically principled way to identify, online, the occurrence, timing, and mode of such change points in the large-scale patterns of interactions by formalizing this problem inside a probabilistic framework. Change points, in our paradigm, are moments in time when an estimated probability distribution over networks undergoes a major change in shape. Not every one of these transition points is that simple to find. With synthetic data that had known structure and change points, found that reliable detection was limited to changes of a sufficiently enough size. In addition, discovered that it was more challenging to precisely identify the changes linked to the "fragmentation" of one or more communities or the "merger" of two communities, as opposed to the "formation" of one community splitting into two or numerous singletons joining together to form a new community. This discrepancy in the detectability of different network alterations begs the concerns of how difficult this task is to do with more information like edge weights and if more advanced algorithms can completely eradicate these discrepancies.

Nevertheless, even for significant structural alterations, change-point approaches based on network metrics such as the clustering coefficient, mean degree, or mean geodesic path length underperformed and produced high false negative rates. The reason for this low performance is probably that generative models rely on a lot of specific information that is discarded by network measures. Compared to network-measure approaches, our approach showed very good results when applied to two high-resolution dynamic social networks, recreating the timing of many more known external "shock" events from network data alone.

Our current implementation's computational overhead is attributed to the MCMC process that employed to determine the hierarchical structure. The suggests a more scalable method for determining a hierarchy through a greedy approach that may naturally be used to our change-point detection. But it's crucial to comprehend the trade-off between scalability and accuracy, and think this would be a fascinating and helpful area to pursue in the future.

While the GHRG model produced good outcome, any generative model, such as the Kronecker product graph model or the stochastic block model, may theoretically be employed in its place. In a similar vein, the change-point identification problem might benefit from an adaptation of the recent work in graph hypothesis testing. Nonetheless, two crucial features of the GHRG model for change point identification are its interpretability and the way it dynamically adjusts its dendrogram structure to meet the network by adding or deleting levels as the network expands.. This approach to change-point detection, when combined with the promising results on both synthetic and real-world data, holds great potential for wide-ranging applications, possibly most notably in social networks, where interpretability plays a critical role in bridging theories about the underlying social dynamics driving network evolution.

IV. CONCLUSION

This paper proposed method detecting change points in evolving networks. The “hierarchical random graph model with a Bayesian hypothesis test” outperforms several previously used alternatives in terms of accuracy. EQNN method is used to change-point detection and aiming to identify changes in the expansive architecture of dynamic networks. Overall, the conclusion underscores the significance of the proposed method in advancing the field of detecting change points in evolving networks and its potential for broad application in understanding the dynamics of network evolution. Using the MATLAB working environment, the proposed method's performance is assessed and contrasted with that of other current approaches. The proposed method provides better results than existing methods such as GNN, CNN and MPNN. The proposed method yields error value 0.5% compared to other existing methods the values are 0.9%, 1.3% and 1.7% respectively.

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