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A SURVEY ON NETWORK EMBEDDING COGNITIVE RADIO ENVIRONMENT

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Abstract:

Network embedding assigns nodes in a network to low dimensional representations and effectively preserves the network structure. Recently, a significant amount of progresses have been made toward this emerging network analysis paradigm. In this survey, we focus on categorizing and then reviewing the current development on network embedding methods, and point out its future research directions. We first summarize the motivation of network embedding. We discuss the classical graph embedding algorithms on cognitive radio environment and their relationship with network embedding. Afterwards and primarily, we provide a comprehensive overview of a large number of network embedding methods in a systematic manner, covering the structure and property-preserving network embedding methods, the network embedding methods with side information and the advanced information preserving network embedding methods. Moreover, several evaluation approaches for network embedding and some useful online resources, including the network data sets and software, are reviewed, too. Finally, we discuss the framework of exploiting these network embedding methods to build an effective system and point out some potential future directions.

Keywords — **Network embedding, Radio Environment.**

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I. INTRODUCTION

Many complex systems take the form of networks, such as social networks, biological networks, and information networks. It is well recognized that network data is often sophisticated and thus is challenging to deal with. To process network data effectively, the first critical challenge is to find effective network data representation, that is, how to represent networks concisely so that advanced analytic tasks, such as pattern discovery, analysis and prediction, can be conducted efficiently in both time and space. Traditionally, we usually represent a network as a graph G = hV, Ei, where V is a vertex set representing the nodes in a network, and E is an edge set representing the relationships among the nodes. For large networks, such as those with billions of nodes, the traditional network representation poses several challenges to network processing and analysis.

High computational complexity: The nodes in a network are related to each other to a certain degree, encoded by the edge set E in the traditional network representation. These relationships cause most of the network processing or analysis algorithms either iterative or combinatorial computation steps, which result in high computational complexity. For

example, a popular way is to use the shortest or average path length between two nodes to represent their distance. To compute such a distance using the traditional network representation, we have to enumerate many possible paths between two nodes, which is in nature a combinatorial problem. As another example, many studies assume that a node with links to important nodes tends to be important, and vice versa. In order to evaluate the importance of a node using the traditional network representation, we have to iteratively conduct a stochastic node traversal process until reaching a convergence. Such methods using the traditional network representation result in high computational complexity that prevents them from being applicable to large-scale real-world networks.

Low parallelizability: Parallel and distributed computing is de facto to process and analyze large-scale data. Network data represented in the traditional way, however, casts severe difficulties to design and implementation of parallel and distributed algorithms. The bottleneck is that nodes in a network are coupled to each other explicitly reflected by E. Thus, distributing different nodes in different shards or servers often causes demandingly high communication cost among servers, and holds back speed-up ratio. Although some limited progress is made on graph parallelization by subtly segmenting large-scale graphs , the luck of these methods heavily depends on the topological characteristics of the underlying graphs

2. LITERATURE REVIEW.

Radio Spectrum has many dimensions inclusive of: space, time, frequency, polarization, energy of signal and interference. The static spectrum control has many challenges to provide spectrum utilization to specific users in different regions.So the idea of DSA developed in CR's. it's far rightly discovered that spectrum shortage changed into the byproduct of the antiquated spectrum management and although a big part of top spectrum changed into assigned, allotted, it remained extraordinarily underutilized. The static spectrum has barrier to access in many spectrum or multi dimensions to provide offerings to rapidly growing call for of spectrum. The Wi-Fi networks of these days can be labeled into two wide classes Cellular, infrastructure primarily based networks characterized with the aid of a entity known as base station imparting a centralized switching factor for communication from devices in a geographical location. Peer-to-peer or advert hoc networks in which communicating nodes do not depend on a centralized node.

3.MODULES

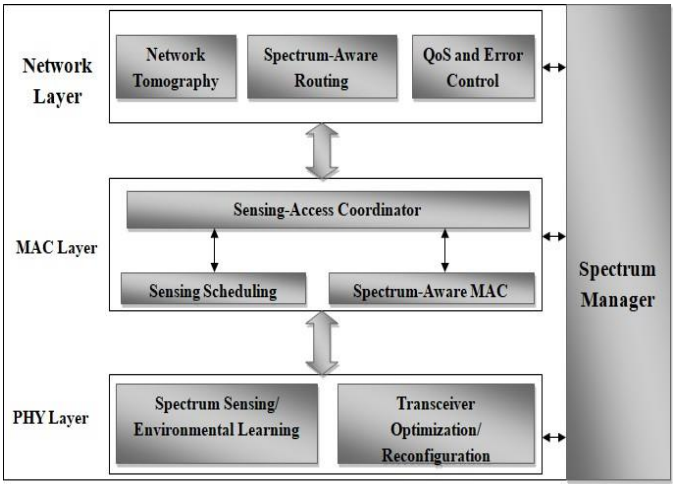
A. NETWORK CONSUTRUCTION MODULE:

In this module the network embedding is to transform the original network space into a low-dimensional vector space. The intrinsic problem is to learn a mapping function between these two spaces. Some methods, like matrix factorization, assume the mapping function to be linear. However, the formation process of a network is complicated and highly nonlinear, thus a linear function may not be adequate to map the original network to an embedding space. If seeking for an effective non-linear function learning model, deep neural networks are certainly useful options because of their huge successes in other fields. The key challenges are how to make deep models fit network data, and how to impose network structure and property-level constraints on deep models. Some representative methods, such as SDNE , SDAE , and SiNE , propose deep learning models for network embedding to address these challenges. At the same time, deep neural networks are also well known for their advantages in providing end-to-end solutions.

B. MATRIX FACTORIZATION ROUTE ANALYSIS MODULE:

In this module the adjacency matrix is commonly used to represent the topology of a network, where each column and each row represent a node, and the matrix entries indicate the relationships among nodes. We can simply use a row vector or column vector as the vector representation of a node, but the formed

representation space is N-dimensional, where N is the total number of nodes. Network embedding, aiming to learn a low-dimensional vector space for a network, is eventually to find a low-rank space to represent a network, in contrast with the N-dimensional space. In this sense, matrix factorization methods, with the same goal of learning low rank space for the original matrix, can naturally be applied to solve this problem. In the series of matrix factorization models, Singular Value Decomposition (SVD) is commonly used in network embedding due to its optimality for low-rank approximation. Non-negative matrix factorization is often used because of its advantages as an additive model.



C. BAND MAJOR DIFFERENCES MAANGEMENT MODULE:

In this module that helps Network embedding and graph embedding have substantial differences in objective and assumptions. As mentioned before, network embedding has two goals, i.e. reconstructing original networks and support network inference. The objective functions of graph embedding methods mainly target the goal of graph reconstruction. As discussed before, the embedding space learned for network reconstruction is not necessarily good for network inference. Therefore, graph embedding can be regarded as a special case of network embedding, and the recent research progress on network embedding pays more attention to network inference. Moreover, graph embedding mostly works on graphs constructed from feature represented data sets, where the proximity among nodes encoded by the edge weights are well defined in the original feature space. In contrast, network embedding mostly works on naturally formed networks, such as social networks, biology networks, and e-commerce networks.

4. EXISTING SYSTEM

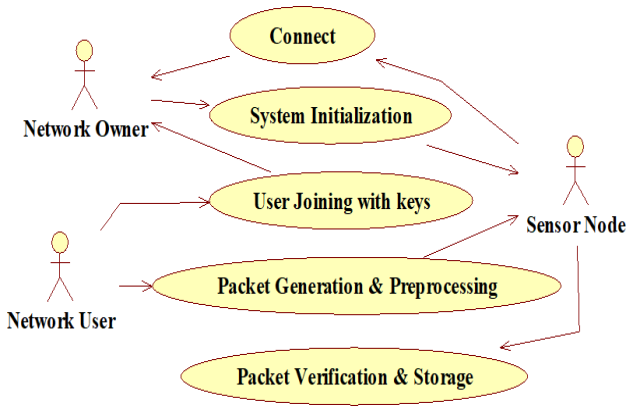
The existent adaptation mechanisms system are usually reactive, they solely react when a tangle happens. This for the most part limits the network ability to produce intelligent and efficient solutions, also with regard to inexperienced networking and advantageous business models. Cognitive Radio Networks (CRNs) give the rise of spectrum utilization by using unused or less used spectrum. Unauthorized users have access to licenced spectrum, below the condition that the interference perceived by the authorized users is lowest.Taking the network node classification problem as an example, if we have the labels of some network nodes, We can design a solution with network structure as input, node labels as supervised information, and embedding representation.As latent middle layer, and the resulted network embedding is specific for node classification.

5. PROPOSED SYSTEM

The most effective way of spectrum sensing is to directly detect the primary Rx, because it is the Rx of a PU system that should be protected. In general, the PU systems can be divided into the following two categories: 1) One-way communication systems and 2) Two-way communication systems. One-way communication systems have only one direction communication from the primary Tx to the primary Rx, such as TV and radio broadcasts. The only way of detecting this kind of Rx's is to sense the leakage signals from active Rx's. Two-way communication systems have bidirectional communications, and there are interactions between the Tx and the Rx, which can be used for spectrum sensing. The One(online

Network Embedding) model is a CR user carries out spectrum sensing to discover spectrum holes, i.e., parts of spectrum allocated (licensed) to some PU's however left unused for a particular time. Upon detective work one or multiple spectrum holes, the CR user reconfigures its transmission parameters (e.g., carrier frequency, bandwidth, and modulation scheme) to control within the known spectrum holes. whereas doing thus, the CR user has to often monitor the spectrum on that it operates and quickly vacate it whenever the Pus become active.

6. RESULTS



In this paper, proposed approach considers In this module Network structures can be categorized into different groups that present at different granularities. The commonly exploited network structures in network embedding include neighborhood structure, high-order node proximity and network communities. Deep Walk is proposed for learning the representations of nodes in a network, which is able to preserve the neighbor structures of nodes. Deep Walk discovers that the distribution of nodes appearing in short random walks is similar to the distribution of words in natural language. Motivated by this observation, Skip- Gram model, a widely used word representation learning model, is adopted by Deep Walk to learn the representations of nodesDeep Walk adopts a truncated random walk on a network to generate a set of walk sequences. For each walk sequence s = fv1; v2; :::; vsg, following Skip-Gram, Deep Walk aims to maximize the probability of the neighbors of node vi in this walk sequence

7. CONCLUSION

This is perhaps intuitive due to the decreased occupancy of these bands but illustrates a wide variation between bands that could be explored further with available data from other bands. If the CR operates across bands, then taking several bands together will offer a larger additional call volume than the sum of the call volumes achieved by the consideration of isolated bands This is due to the non-linearity of the BHT formula, where larger number of lines permits a higher percentage of traffic volume than a smaller number of lines. The DECT band was found to be not worthwhile for CR considerations, since in DECT a combined OFDMA / TDD scheme will show large parts of the spectrum occupied even for a low duty cycle, i.e. a low occupancy. Since the CR algorithm used offers only sensing in the frequency domain, TDD schemes with empty slots currently cannot be exploited by the simulated system

REFERENCES.

[1] Jai Sukh Paul Singh, Jasvir Singh, A.S. Kang, "Cognitive Radio: State of Research Domain in Next Generation Wireless Networks - A Critical Analysis", International Journal of Computer Applications (0975 – 8887) Volume 74– No.10, July 2018.

[2] Blaine Chamberlain And Geogette Jordan" Applications of Wireless Sensors in Monitoring Indoor Air Quality in the Classroom Environment", Research Experiences for Teachers in Sensor Networks, Summer Internship 2019,University of North Texas,NSF-1132585.

[3] Douglas S. J. De Couto, Daniel Aguayo, John Bicket, and Robert Morris, "A high-throughput path metric for multi-hop wireless routing", Wireless Networks, vol. 11, no. 4, pp. 419–434, 2017.

[4] Prof. B.N. Jagdale and Prof. Pragati Patil, "Analysis and Comparison of Distance Vector, DSDV and AODV Protocol of MANET", International Journal of Distributed and Parallel Systems (IJDPS),Vol.3, No.2, March 2018.

[5] H. Yang, Y. Qin, G. Feng, and H. Ci, "Online monitoring of geological CO2 storage and leakage based on wireless sensor networks," IEEE Sensors Journal, vol. 13, no. 2, pp. 556–562, Feb. 2018.