JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

MACHINE LEARNING TECHNIQUES FOR 5G AND BEYOND USING PSO ALGORITHM

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ABSTRACT

Network embedding successfully maintains the network structure by assigning network nodes to low dimensional representations. A considerable amount of progress has recently been achieved in the direction of this new paradigm for network research. In this study, we concentrate on classifying, analyzing, and pointing out the future directions for network embedding techniques research. We begin by summarizing the purpose of network embedding. We talk about network embedding and how it relates to traditional graph embedding methods in a cognitive radio context. Following that, we give a thorough overview of a variety of network embedding techniques in a methodical way, including advanced information preserving network embedding techniques, network embedding techniques with side information, and approaches that preserve structure and properties. Additionally, many methods of network embedding assessment as well as certain practical online tools, such as network data sets and software, are explored. In our last section, we cover the foundation for utilizing these network embedding techniques to create a successful system and identify some possible future paths.

1. INTRODUCTION

5G technology and the next B5G era have driven previously unheard-of improvements in communication networks, bringing in a new age of connectedness marked by faster data rates, reduced latency, and improved dependability. Machine learning techniques have become essential tools in managing resource allocation, optimizing network performance, and mitigating the complexities brought about by the dynamic and heterogeneous nature of 5G and beyond networks, helping to fully realize the potential of these transformative technologies. The use of machine learning not only improves network operations efficiency but also enables intelligent and adaptive decision-making processes, which greatly aids in the achievement of the lofty objectives established for the subsequent wave of wireless communication.

1.1 5G

The fifth generation of wireless communication, often known as 5G, promises a major leap forward in connectivity. 5G technology, introduced to meet the growing needs of our hyper-connected society, outperforms its predecessors by offering much faster data rates, ultra-low latency, and unparalleled network capacity. 5G has the potential to disrupt industries and boost new technologies such as the Internet of Things (IoT) and augmented reality, changing the way we communicate and interact with our increasingly digitalized world. Its strong capabilities promise to open up new opportunities in industries ranging from healthcare and transportation to smart cities, positioning 5G as a critical driver for the next wave of technological innovation and global connection.

1.2 BEYOND 5G (B5G)

Beyond 5G (B5G) is at the vanguard of the changing landscape of wireless communication, ushering in a new age of connection that goes beyond the capabilities of 5G technology. As a conceptual foundation for future developments, B5G seeks to meet the growing needs of an increasingly linked world by pushing the limits of data throughput, latency, and network stability. B5G, envisioned as the successor to 5G, aims to uncover transformational potential in communication networks, promoting innovations that cross industries and redefine how people experience connectivity.

1.3 MACHINE LEARNING

Machine learning (ML) is an area of artificial intelligence (AI) that allows computers to learn and improve via experience without being explicitly programmed. It focuses on the creation of algorithms and models that allow computers to automatically discover patterns, make predictions, and improve their performance over time as they process and analyze data. Machine learning applications are broad, including picture and audio recognition, natural language processing, recommendation systems, and predictive analytics. The iterative learning process helps computers to improve their comprehension and decision-making abilities, making machine learning an important tool for addressing complicated issues and extracting useful insights from massive datasets across sectors.

2. LITERATURE SURVEY

In this research, Walid Saad [1] et al. have proposed The steady rollout of 5G cellular infrastructure is revealing more and more of the system's intrinsic shortcomings in comparison to its initial intent as a facilitator for Internet of Everything applications. The limitations of 5G are presently driving global efforts to define the next generation of 6G wireless networks, which will be able to incorporate far-reaching applications such as haptics and extended reality, as well as autonomous systems. The core architectural and performance components of the system are still largely unknown, despite recent 6G initiatives1. In this article, we explain the fundamental principles of a 6G system, offering a comprehensive and forward-looking view. According to our predictions, 6G will not just include the investigation of more high-frequency band spectrum; rather, it will involve the confluence of many emerging technology trends propelled by intriguing underlying services. To that purpose, we first list the main applications and corresponding technology advances that are driving 6G systems. Next, we reveal the objective 6G performance criteria for a new set of service classes that we propose. Next, we determine which technologies are necessary to provide the recently launched 6G services and present a thorough research program that makes use of these technologies. We wrap up by offering specific suggestions for the 6G roadmap. A disruptive sixth generation (6G) wireless system, whose design is intrinsically tuned to the performance needs of the aforementioned IoE applications and their associated technology advances, is required to overcome these obstacles and spur the implementation of innovative IoE services.

In this research, Faisal Tariq [2] et al. have proposed While 5G is being tested globally and is expected to be gradually deployed in 2019, researchers are starting to focus on what 6G might look like in ten or more years. Numerous countries have already launched initiatives to investigate potential 6G technologies. This essay tries to expand the scope of 5G to more ambitious future scenarios and makes predictions about the forward-thinking technologies that could bring about the necessary step adjustments to make 6G possible. The amount of mobile data traffic worldwide has increased exponentially over the last ten years; in 2021, data volume is expected to rise by a factor of 23 when compared to the total amount of Internet traffic worldwide in 2005. As shown in Fig. 1, the International Telecommunication Union (ITU) forecasted that by 2030, monthly mobile data traffic would reach an incredible 5 zettabytes (ZB) due to the pattern of exponential development continuing. The most recent effort to advance mobile communications technology to satisfy the needs for the next ten years is the fifth generation (5G). By 2030, 5G is predicted to reach its limitations, but the race is still on.

In his article, Mostafa Zaman Chowdhury [3] and colleagues have suggested Over the last two decades, there has been an exponential increase in demand for wireless communication. Global deployment of fifth-generation (5G) communications is imminent, with a much larger feature set than fourth-generation communications. With the complete assistance of artificial intelligence, the sixth-generation (6G) system is anticipated to usher in a new age of wireless communication somewhere between 2027 and 2030. faster system capacity, faster data rate, lower latency, higher security, and better quality of service (QoS) in comparison to the 5G system are some of the main concerns that need to be solved beyond 5G. The network architecture and future state of 6G wireless communication are presented in this study. This article discusses cutting-edge technologies that can help the development of the 6G architecture ensure the quality of service, including artificial intelligence, terahertz communications, wireless optical technology

In this study, Edward O'Dwyer[4] et al. have suggested It has long been known that sophisticated methods are required to manage and coordinate the wide variety of supply and conversion technologies as well as demand applications within the framework of the Smart City. Embedded computational intelligence algorithms and the widespread proliferation of sensors may assist in addressing many of the technological obstacles related to this energy systems integration issue. However, obstacles persist because appropriate techniques are required to manage intricate networks of players, sometimes with conflicting goals, and to make judgments about the design and operation of systems spanning a broad range of characteristics and time horizons. This analysis examines the latest advancements in the smart energy industry, emphasizing strategies in the primary application domains and pertinent real-world examples. It also identifies some of the major obstacles the industry is now facing and lays out its future directions. Additionally, anticipated applications together with the necessary 6G communication technology are shown.

In this research, Bin Li[5] et al., has proposed The main issue for 5G and beyond 5G (B5G) is to provide ubiquitous connection to a variety of device types. Unmanned aerial vehicles (UAVs) are anticipated to play a significant role in the next generation of wireless networks, which may enable high-speed communications and wireless broadcasting. UAVs provide notable advantages over fixed infrastructure communications, including strong line-of-sight (LoS) connection connections, flexible deployment, and more design flexibility due to controlled mobility. This study presents a thorough review of UAV communication with 5G and B5G wireless networks. First, we provide some background information on space-air-ground integrated networks and associated research problems that the evolving integrated network architecture is facing. After that, we provide a thorough analysis of many 5G strategies based on UAV platforms, classifying them according to several categories such as the physical layer, network layer, joint communication, computation, and caching. Furthermore, a large number of open research issues are listed and suggested as potential areas for further investigation. IoT devices are becoming more and more mobile, thus a reliable communication system with high capacity and broadband connection is required to handle a large number of IoT devices. Flying UAVs have lately drawn a lot of scientific attention due to their ability to accomplish these needs.

3. PROBLEM DEFINITION

The rapid evolution of wireless communication systems from the current fifth generation (5G) to the anticipated sixth generation (6G) brings forth a promising future, marked by enhanced connectivity and efficiency. However, the seamless integration of Artificial Intelligence (AI) and Machine Learning (ML) into every layer of the 6G wireless infrastructure introduces complex challenges. These challenges include the potential increase in system complexity and overhead, concerns related to privacy and security, limitations in obtaining diverse and representative training data for ML models, and the risk of elevated energy consumption. Addressing these is paramount to harness the full potential of AI and ML in 6G networks while ensuring the reliability, security, and sustainability of future wireless communication systems.

4. EXISTING SYSTEM

Wireless communication systems are extremely important in today's culture for applications such as entertainment, business, commerce, health and safety. These systems are constantly changing from one generation to the next, and we are presently seeing the implementation of fifth-generation (5G) wireless networks across the world. Academics and industry are already contemplating the sixth generation (6G) of wireless technologies, which will follow the fifth generation. One of the most important components of 6G systems will be the usage of Artificial Intelligence (AI) and Machine Learning (ML) for wireless networks. Every component and building element of a wireless system that we are already familiar with from our understanding of wireless technologies up to 5G, such as the physical, network, and application layers, will use one or more AI/ML techniques. This overview article provides an up-to-date analysis of future wireless system ideas, such as 6G, as well as the importance of machine learning techniques in these systems. In specifically, we describe a conceptual model for 6G and demonstrate the application and function of machine learning techniques in each layer of the model. In the context of wireless communication networks, we examine various classical and modern machine learning approaches, including supervised and unsupervised learning, Reinforcement Learning (RL), Deep Learning (DL), and Federated Learning (FL). We finish the presentation by discussing possible prospective applications and research difficulties in the field of machine learning and artificial intelligence for 6G networks.

5. PROPOSED SYSTEM

Utilizing the Particle Swarm Optimization (PSO) algorithm is the suggested approach. Particle Swarm Optimization (PSO) is a computational approach used in computer science that optimizes a problem by repeatedly attempting to improve a candidate solution in relation to a specified quality metric. After the algorithm was made simpler, optimization was seen to be occurring. When compared to other algorithms and heuristic optimization approaches, the PSO algorithm's key benefits may be summed up as follows: simple idea, straightforward implementation, resilience to control parameters, and computing efficiency. The suggested system is a thorough framework for network analysis intended to provide cutting-edge understanding of intricate network architectures. It is composed of several interrelated modules that cover important facets of network analysis. Using matrix factorization techniques, the Network Construction Module produces a structured representation of the network. Then, by examining route-level specifics, the Matrix Factorization Route Analysis Module reveals hidden patterns and maximizes connectedness. The Band Major Differences Management Module ensures accurate and flexible analysis by managing variances within designated bands in an effective manner. Lastly, nodes are intelligently grouped and data shared inside node clusters by the Structure Preserving Network Node Grouping and Data Sharing Module, which simultaneously maintains network structure. When combined, these modules provide a flexible system that can handle data discrepancies, optimize network pathways, offer subtle insights, and maintain the natural structure of intricate networks.

5.1 NETWORK CONSUTRUCTION MODULE

The network embedding used in this module is used to convert the original network space into a low-dimensional vector space. Finding a mapping function between these two spaces is the fundamental issue. Some techniques presuppose that the mapping function be linear, such as matrix factorization. But because a network forms in a complex, highly nonlinear way, a linear function might not be sufficient to transfer the original network to an embedding space. Deep neural networks are undoubtedly excellent possibilities if looking for an efficient non-linear function learning model because of their enormous accomplishments in other domains.

5.2 MATRIX FACTORIZATION ROUTE ANALYSIS MODULES

The adjacency matrix, where each column and each row represent a node and the matrix entries indicate the relationships among nodes, is frequently used in this module to represent the topology of a network. A node can be represented by a row or column vector, but these results in an N-dimensional representation space, where N is the total number of nodes. In contrast to the N-dimensional space, the goal of network embedding, which aims to learn a low-dimensional vector space for a network, is to ultimately find a low-rank space to represent a network. In this sense, the solution to this issue can naturally be achieved by applying matrix factorization techniques, which share the same objective of learning the low rank space for the original matrix. Due to its superiority for low-rank approximation in the family of matrix factorization models, Singular Value Decomposition (SVD) is frequently used in network embedding. The benefits of non-negative matrix factorization as an additive model make it widely used.

5.3 BAND MAJOR DIFFERENCES MAANGEMENT MODULE

This module's assistance the assumptions and goals of network embedding and graph embedding are very different. As previously indicated, network embedding aims to facilitate network inference as well as reconstitute the original networks. Reconstruction of the graph is the primary purpose of graph embedding methods. The embedding space discovered for network reconstruction is not always suitable for network inference, as was previously noted. As a result, graph embedding may be thought of as a particular instance of network embedding, and recent advancements in network embedding research have focused more on network inference.

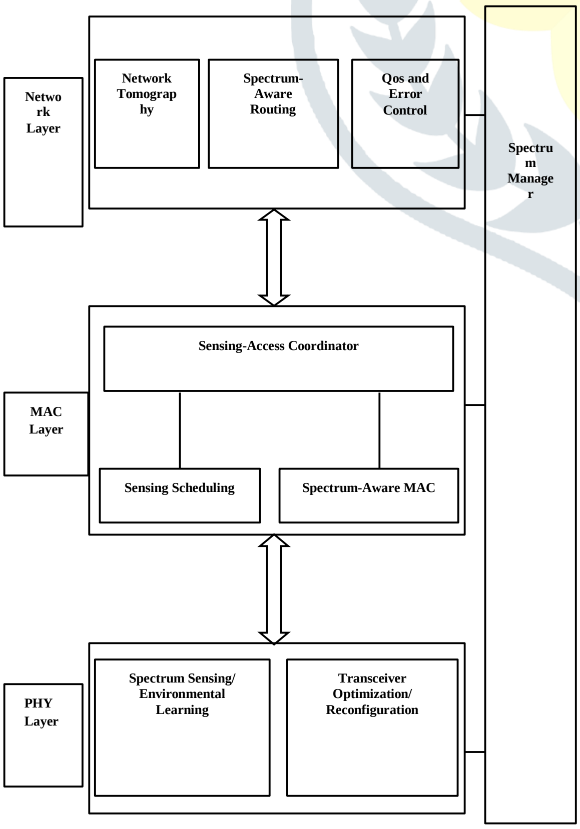

Figure 1 System Architecture

5.4 STRUCTURE PRESERVING NETWORK NODE GROUPING AND DATA SHARING MODULE:

In this module, network architectures may be divided into several categories and shown at various granularities. For learning node representations in a network that can maintain node neighbor structures, Deep Walk is presented. In a brief random walk, Deep Walk finds that the distribution of nodes resembles the distribution of words in natural language

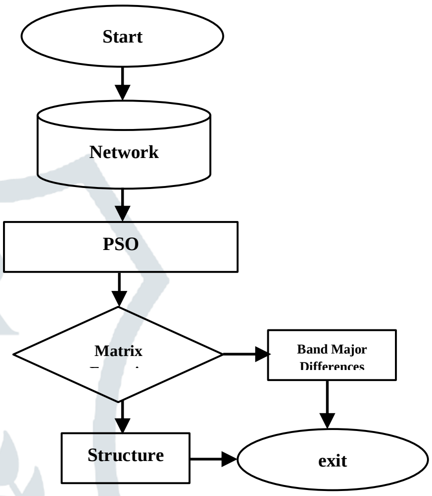

Figure 2. Flow diagram

6. ALGORITHM DETAILS

Particle swarm optimization

The basic principles in "classical" PSO are very simple. A set of moving particles (the swarm) will be set into the search area. Each particle has a position vector of Xi and a velocity vector Vi. The position vector Xi and the velocity vector Vi of the i th particle in the n-dimensional search area could be represented as Xi= (xi1, xi2, xin) and Vi= (vi1, vi2, vin) respectively. The memory with which each particle finds the best position is called Pbest and best location is known as Gbest. Assume Pbest = (xi1Pbest, xi2Pbest, ..., xin(Pbest) and Gbest = (x1Gbest, x2Gbest, ..., xn(Gbest)) be the best positions of the individual i and all the individuals. At each level, the velocity of the i th particle will be updated according to the following equation in the PSO algorithm.

$$Vik+1=\omega Vik+c1r1\times Pbestik-Xik \quad +c2r2\times \quad Gbestk-Xik \ldots\ldots\ldots\ldots (1)$$

In this velocity updating process, the acceleration coefficients c1, c2 and the inertia weight ω are predefined and r1, r2 are uniformly generated random numbers in the range of [0, 1]. In general, the inertia weight ω is set according to the following equation:

$$\omega= \omega max-\omega max-\omega miniterm ax\times iter\ldots\ldots\ldots (2)$$

The approach used by Eq (2) is called the "inertia weight approach. With the help of above equation diversification characteristic is gradually decreased and a specific velocity, which gradually moves through the current searching point close to Pbest and Gbest, can be calculated. Each individual moves from the present position to the next one by the modified velocity in Eq (1) using the following equation:

$Xik+1=Xik+Vik+1$……… (3)

Initialize particle;

End;

Do for each particle;

Calculate fitness value;

If the fitness value is better than the best fitness value (pbest) ;

Set current value as the new pbest;

End;

Choose the particle with the best fitness value of all the particles as the gbest;

For each particle;

Calculate particle velocity according equation; Update particle position according equation; End;

While maximum iterations or minimum error criteria are not attained;

7. RESULT AND ANALYSIS

The transmission channel in Cognitive Radio Networks is likened to the main users (PUs), whereas secondary users (SUs) can only access the channel opportunistically when the PUs are inactive, that is, when the PUs are not using the channel. A SU transmission must be stopped every time a PU becomes active since the SUs use the channel opportunistically. The amount of time needed to finish the SU's carrier (carrier Time) relies on the quantity and size of the PUs' transmissions when an SU needs to send several packets (for example, in a record transmission) or when a packet may be too large.

ALGORITHM	ACCURACY
Reinforcement	75
Pso	81

Figure 3 comparison table

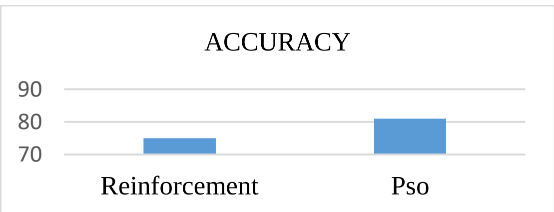

Figure 4comparison graph

7. CONCLUSION

Currently, 2G users will create an unquestionable level of habitation that may essentially rule out CR. However, if the switchover to 3G services continues, the band may have reduced habitation rates and hence be more suited to a variety of CR services. Our suggested approach offers improved accuracy and optimization. The GSM findings exhibit substantial fluctuation depending on the estimated degree of occupancy, although they could be appropriate for CR services that require "silent hours." The high degree of occupancy now being created by 2G users may leave little opportunity for CR. The GSM band, on the other hand, may have lower occupancy levels and hence be more appropriate for a variety of CR services if the amount of migration to 3G services persists. Results for CR similar to those predicted for the UMTS expansion band scenario will occur should GSM usage decline to the point that operators wish to re-farm the GSM bands to 3G services. In every case, the UMTS Expansion bands outperformed the GSM frequency in terms of call volume

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