Artificial Intelligence Driven 5G and Beyond Networks

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Abstract—5G networks and beyond are expected to meet numerous service requirements in various aspects of our daily lives. At the same time, the functional complexity of 5G telecommunication networks increases by an order of magnitude compared to existing networks. 5G data rates are dramatically faster, connection density is higher, and latency is much lower, among other improvements. An efficient 5G network cannot be complete without incorporating artificial intelligence (AI) techniques. All this requires the use of new technologies, including artificial intelligence, to ensure the stable operation of telecommunication networks, methodology, system analysis, and key results. Scientific tasks for 5G communication networks are identified where the use of artificial intelligence, including machine and deep learning, seems appropriate. Practical Relevance. The results of the work may be useful in training in networks and telecommunication systems and in defining new scientific tasks for PhD students.

Keywords—5G, machine learning, deep leaning, prediction.

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ИСКУССТВЕННЫЙ ИНТЕЛЛЕКТ КАК ДВИЖУЩАЯ СИЛА ДЛЯ СЕТЕЙ СВЯЗИ ПЯТОГО И ПОСЛЕДУЮЩИХ ПОКОЛЕНИЙ

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Аннотация—Сети связи пятого (5G) и последующих поколений будут соответствовать многочисленным требованиям к услугам в различных аспектах нашей повседневной жизни. При этом функциональная сложность телекоммуникационных сетей 5G возрастает на порядок по сравнению с существующими сетями. Основные достижения в сетях пятого поколения состоят в том, что скорость передачи данных значительно выше, плотность устройств достигает 1 млн на кв. км, а задержка из конца в конец намного ниже. Эффективность сети 5G в существенной степени зависит от применения методов искусственного интеллекта (ИИ). В статье определены научные задачи для сетей связи 5G для тех приложений, где использование искусственного интеллекта, включая машинное и глубокое обучение, представляется целесообразным. Практическая значимость работы состоит в том, что результаты статьи могут быть полезны при обучении технологиям ИИ в области с сетей и систем телекоммуникаций, а также при постановке новых научных задач перед аспирантами.

Ключевые слова—5G, машинное обучение, глубокое обучение, прогнозирование.

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Introduction

5G and beyond networks are expected to meet various service requirements in different areas of our daily lives, from housing to work and leisure to transportation. Due to the enormous range of 5G requirements in terms of user experience, efficiency, performance, and complex network environments, the design and optimization of 5G networks becomes a major challenge. The future 5G network requires robust intelligent algorithms to adapt network protocols and resource management for different services in different scenarios. Artificial intelligence (AI), defined as any process or device that recognizes its environment and takes actions that maximize the chances of success for a predefined goal, is a practical solution for designing emerging complex communication systems. Recent developments in deep learning, convolutional neural networks, and reinforcement learning show promise for solving very complex problems that were previously considered intractable [1, 2, 3, 4].

There is now an opportunity to incorporate AI technology into 5G and beyond networks to address optimal physical layer design, complex decision making, network management, and resource optimization in these networks. In addition, the emerging Big Data technology provides us with an excellent opportunity to study the fundamental characteristics of wireless networks and help us gain a clearer and deeper knowledge of the behavior of 5G wireless networks[1] [5].

In studying 5G wireless technologies and communication systems, AI will be a robust tool and an interesting research topic with several potential application areas, such as wireless signal processing, channel modeling, and resource management. Here, we first introduce some popular AI techniques. AI techniques include interdisciplinary techniques such as machine learning (supervised learning, unsupervised learning, and reinforced learning), deep learning, improvement theory, game theory, and metalogics. Among them, machine learning and deep learning are the most common AI subfields that are widely used in wireless networks[2] [5].

The deployment of 5G networks is fraught with many difficulties. One way to overcome them is to integrate artificial intelligence into the networks. More than 50 % of mobile companies have integrated AI into 5G networks by the end of 2020. The main focus of AI integration is to reduce capital expenditures, optimize network performance, and build new revenue streams. 55 % of decision makers said AI is already being used to improve customer service and enhance the customer experience by improving network quality and offering personalized services. 70% believe that using AI in network planning is the best way to recoup the investment required to transition networks to 5G. 64 % of survey respondents will focus their AI efforts on network performance management. Other areas where mobile decision makers are looking to invest in AI include SLA, product lifecycles, networks and revenue. Of course, integrating AI into 5G networks presents some challenges. Effective mechanisms must be developed to collect, structure, and analyze the enormous amounts of data that AI

[1] https://www.deepsig.ai/how-artificial-intelligence-improves-5g-wireless-capabilities
[2] Ibid.

accumulates. For this reason, the early AI adopters who find solutions to these challenges will clearly be ahead of the game when it comes to networking 5G networks[3].

Artificial intelligence (AI) is emerging as a critical component needed to understand the many data sets collected and make them commercially valuable. AI can support data analysis from the Internet of Things (IoT), where the system can perform tasks or improve intelligent information. In addition, AI in IoT devices can identify data, make decisions, and work with this information without user intervention [6].

Machine learning (ML) is the method that deals with the development of algorithms that can learn from information and make predictions. Moreover, modern central processing unit technology (CPU) enables effective implementation of AI algorithms. However, the volume of traffic is increasing, and the heterogeneity of traffic is increasing. The Internet of Things (IoT) and ultra-reliable, low-latency communications bring a variety of demands that require greater efficiency in quality of service (QoS) decisions, as current QoS technologies cannot achieve the desired level. Most provisions are needed to predict load and delay for specific facilities, taking into account geography and dynamics such as subscriber movement and incredible speeds. Operators also need an overall system that can make predictions about infrastructure evaluation, taking into account the adoption of new technologies that enable new online services and the associated expected changes in people's lifestyles [7].

AI plays a critical role in fifth-generation (5G) networks [8, 9], such as the IoT and tactile Internet, because it can quickly extract insights from data. ML can automatically discover models and anomalies in the information generated by sensors and smart devices. AI technologies extend ML strategies applied to smart IoT devices to make complex decisions based on recognition patterns, self-learning, self-healing, context awareness, and autonomous decision-making. These include and influence future applications of dual digital models and continuous learning that play a role in autonomous vehicle applications, IoT, and predictive maintenance.

AI is widely used in wireless networks, e. g., in processing and recognizing information and data streams [10, 11]. It can also predict and process historical data series, geographic and positional information in real time, which is essential in almost all technology areas. It affects the applications, evaluation tools, computational level, data processing methods, and interface control capabilities in virtually all areas of information technology (IT). 5G will increase the speed and combination of other technologies, while AI will enable machines and systems to work intelligently like humans. In summary, 5G will accelerate services in the cloud while rapidly analyzing and learning from the same data. Wireless communication is a driving force in promoting economic, technical, social, security and study conditions. It also supports the growth factor to meet the needs of the new generation. Researchers are constantly striving to develop new wireless communication technologies and mechanisms to facilitate human life, such as the advancement of IoT, 5G, transportation networks, tactile Internet, and so on.

Due to the advances in computing capabilities and ML techniques such as Deep Learning (DL), AI is performing well in various applications such as security, network data processing, etc. Undoubtedly, AI reduces user intervention and provides reliable

[3] Ibid.

results, regardless of the application domain. Therefore, the advancement of AI can also provide innovation and novelty for 5G networks to manage the network efficiently. With additional AI and automation layers that provide zero-touch and end-to-end, 5G will provide excellent opportunities to increase revenue. Today, many researchers are interested in integrating AI and wireless communications, which is reflected in the standardization plans [12, 13].

The growth of IoT requires the installation of various applications with complex operational requirements. Delays are one of the most critical measures for IoT, especially in network traffic prediction and healthcare monitoring, where urgent situations need to be managed. In IoT applications, intelligent processing and Big Data analytics are the main drivers for development. Data science with IoT is mainly used in various fields where volume, speed, and pattern recognition are concerned. Due to predictive ML analysis, the software can predict both desired and undesired incoming events. Therefore, the system ML detects abnormal behavior and helps to understand and establish long-term trends, which requires continuous correction and monitoring to achieve effectiveness and efficiency in data analysis [14, 15].

There is an obvious convergence between IoT and AI. The IoT can connect objects and devices to leverage the data generated by those devices, while AI can model the intelligent behavior of all types of devices. As IoT systems generate large data sets, AI helps process these data sets and understand the information. However, traditional methods for structured data, analytics and definition processes are unable to effectively manage the massive data flowing in real time from IoT devices. There is a high degree of convergence between IoT and AI. The IoT can connect devices, the data generated by those devices, and AI to model the intelligent behavior of all types of devices. Since IoT devices will produce an enormous amount of information, AI will process and understand this information. However, traditional approaches to structuring information, analytics and specific processes will not allow you to efficiently manage all the information about the entities that make up the IoT in real time. AI-based analytics and responses can be used to determine the optimal value of the information, if any. The proliferation of ML and IoT algorithms can significantly improve the application infrastructure. The use of ML can improve network management to avoid congestion, optimize resource allocation, and examine essential information to make decisions or offload data. ML Methods including artificial neural network (ANN)-based approaches, can effectively store and process large amounts of data [6].

Network information prediction is among the best active areas combining AI studies for information networks. Nowadays, it can be used in various applications and is attracting more and more attention from many researchers. Information prediction is an effective way to ensure the security, reliability and connectivity of selected networks. Many network traffic prediction methods have been proposed and tested, including Internet-based data extraction methods. Many interesting network prediction strategies have been developed to achieve powerful results[4] [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17]. Fig. 1 illustrates an example of IoT traffic prediction using ML techniques.

[4] Ibid.

Fig. 1. Machine learning for IoT traffic prediction

The motivations behind this study include the following

– AI is already being integrated into networks to optimize network performance and the adoption of AI creates new data challenges even as it solves network complexities.

– Optimize quality of service (QoS) requirements and network monitoring to manage resources and ensure security.

– Monitor network availability and activity to identify and eliminate outliers/faults, including security and operational issues.

– The lack of accurate machine learning analysis to achieve adequate performance.

– The computational complexity of challenging problems in optimizing QoS measures.

– Apply techniques to predict time series data, remembering the historical data, and accurately estimate future time series data. They also have the advantage over traditional approaches to time series prediction in that they serve to maximize the accuracy of the learning method over the training iterations. As more data is added to the model, the model becomes smarter and can better estimate traffic volumes, which is important for real-time traffic forecasting. These techniques such as nonlinear autoregressive network with exogenous inputs (NARX) enabled recurrent neural networks (RNNs) and long short-term memory (LSTM) networks enabled deep neural network learning.

Machine Learning for time series prediction

Predicting historical time sequences is an essential aspect of ML; it belongs to supervised learning approaches and is widely used in data science, applied in various domains. Several ML techniques, including regression, ANN, KNN, SVM, random forest, and XGBoost, can be used to predict time series. ML-based forecasting models have found wide application in time series projects required by various organizations to facilitate predictive allocation of time and resources.

ANN can help historical series prediction by eliminating the instantaneous need for extensive feature technology processes, data scaling procedures, and the need for stationarity and differentiation of historical series data. RNN is suitable for supervised learning tasks when data are available in a temporal sequence. It can remember the historical information to estimate future time-series data. The RNN algorithm is trained based on the previous data of the historical series into the input level. The network's connectivity is adapted depending on the difference between the actual and expected outputs over the network. Before configuring the network, the operator must determine the network hidden layers to size and the training termination process.

In prediction, the past information is used to predict what will follow, and the following information is predicted, relying on what happened. The temporal sequence adds a temporal dependency between historical information. This dependency is under limitations and is structured to provide an additional source of information. Historical time sequence prediction is a method of predicting information about a historical series. It expects the following information by analyzing the past information if the future information is similar to the historical information. It can be applied in several use cases, such as resource allocation, network traffic, weather forecasting, control engineering, statistics, signal processing, and business planning. These are just a few of the many possible applications for time series forecasting.

In real-world time series — i. e., forecasting weather, air quality, and network traffic flow are scenarios based on IoT devices, such as detectors — abnormal time form, missing data, high noise, and complicated correlations are multivariate and current limitations of classical prediction techniques. Such methods usually depend on noise-free and perfect information for good performance: missing data, outliers, and other erroneous features are generally not supported. Time series prediction starts with a historical time sequence, and experts investigate the historical information and temporal decomposition models, such as tendencies, seasonal models, periodic models, and symmetry. Various sectors, such as commerce, utilize historical time sequences prediction to assess potential technological complexity and customer needs. Temporal series data models can have many variations and perform various random processes[5] [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17].

A. NARX neural network

NARX represents a nonlinear autoregressive network with external inputs. NARX are dynamical RNN, have return paths surrounding various network connections. NARX networks are based on the auto-regressive with exogenous input (ARX) time series models, commonly used for time series operations, and are considered a nonlinear form of the ARX model. NARX models can simulate various nonlinear dynamic methods; they have been used for multiple problems, including time series simulation. The NARX network uses prior measures of the existing historical time series to make predictions and the previous values of other inputs to make predictions for the target series. NARX is a robust tool suitable for nonlinear modeling systems. Moreover, NARX learns more efficiently than other neural network time series, using a gradient descent learning algorithm. NARX networks have been successfully used in many applications to predict future values of the input signal [2, 3, 13, 14, 15, 21] (fig. 2).

[5] Ibid.

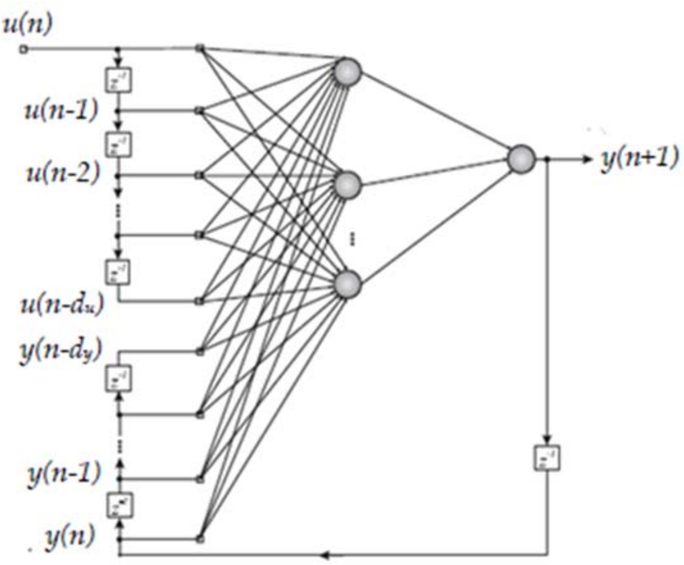

Fig. 2. NARX neural network architecture

B. Deep Learning with LSTM network

Predicting traffic behavior using Deep Learning is significant because it can learn from large amounts of data and identify patterns more accurately than other approaches. Predicting potential traffic enables solutions to improve QoS before failure occurs. Deep neural network learning can be used for predictive analytics, as it uses historical data to make better decisions, resulting in higher accuracy. In addition, expecting a possible massive occurrence of data streams at unusual times, which can most likely be classified as data stream-based attacks, enables a more secure network. Moreover, predicting such large data streams can also eliminate the risk that can disrupt the operation of the IoT system [18, 19].

Network traffic prediction enables operators to take early actions to control traffic load and improve network performance. In addition, traffic forecasting for long time periods enables detailed traffic models to assess future capacity needs, allowing for more accurate planning and better decisions. Forecasting for short time periods (milliseconds to minutes) is related to dynamic resources. Fast and accurate traffic forecasting is an important technique to achieve better efficiency.

To overcome the problems of 5G networks, technologies that improve network traffic prediction accuracy are needed to avoid degradation of system QoS efficiency. Visual technologies must be predictive to avoid weakly interacting solutions; therefore, a variant of traffic prediction is required. Many ML techniques have been proposed so far to improve the accuracy of traffic prediction. One of the best techniques is Deep Learning Neural Network (DNN), which is based on the technique of ANNs. The algorithm has been observed and tested to predict the upcoming traffic data.

Deep Learning (DL) is a special type of multilayer neural network. DL relies on multilayer neural networks and related algorithms that often process large data sets. Some methods are superior to traditional NNs in processing the data of the previous case. RNN is one of the techniques that consist of multiple network loops and are better than traditional ANNs at processing the data from the previous event. Each network in the loop takes the input and information from the previous network, executes the specified process, produces an output, and passes the information to the subsequent network.

Ordinary RNNs are very poor at handling situations where something needs to be "stored" for a long period of time. The learning delay becomes very large when there is no connection between the information needed in the past and the essential principle. The effect of a hidden state or input with step t on subsequent states of the feedback network decreases exponentially. The solutions currently offered in Deep Learning mainly consist of changing and complicating the architecture of a "building block" of the recurrent network. It turns out that instead of a single number affected by all subsequent states, we can construct a special kind of cell in which we explicitly simulate, in one form or another, a "long memory", the processes of writing and reading from this "memory cell", and so on. Of course, such a cell will have not just one set of weights, like a typical neuron, but several, and learning will be more difficult, but in practice it often proves rewarding. Some applications require only new data, while others require more of the previous data. The usual recurrent neural networks lag behind in learning as the gap between the information needed in the past and the key to the requirements increases significantly.

One of the most well-known and widely used structures from each of these cells is a LSTM (*Long Short-Term Memory*); DL with LSTM model is the particular type of RNNs that can learn like predictions. These networks are precisely designed to open the case of long-term dependence of recurrent networks. LSTMs are excellent at storing data over a long period of time. Since a larger amount of information can affect the performance of the model, LSTMs are a natural choice for deployment. The advantages are that LSTMs can be active to support autonomous connections without having to be taken down. Also, the network needs to be trained to decide what information is on the bus, the study, the network and a clear idea of what needs to be stored. You do not have to be afraid to enter new data and destroy important information [1, 10, 11, 12, 16, 17, 18, 19, 20] (fig. 3).

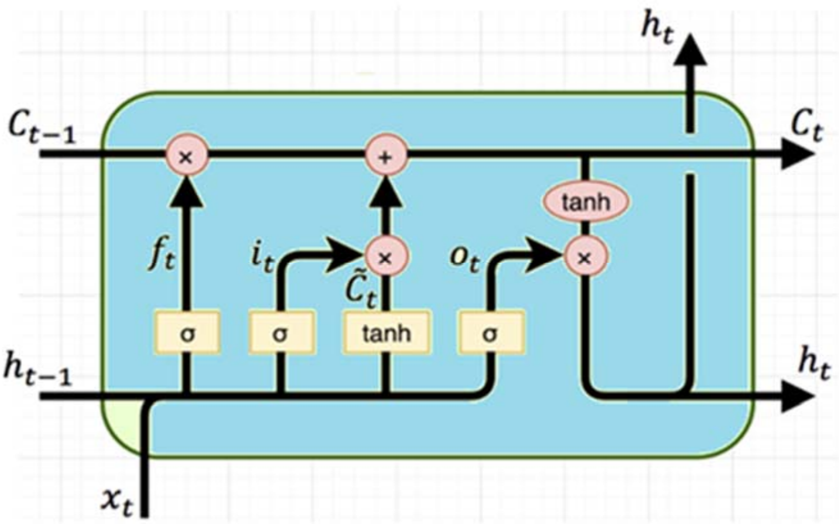

Fig. 3. Basic structure of LSTM cell

Conclusion

In this article, we have provided an overview of combining artificial intelligence with the 5G network. 5G will enable a new era of opportunity for all and will open the creative minds of technology experts as they think about new and innovative ways to improve our businesses and our lives. The combination of AI and machine learning with the 5G network will make things even more interesting.

From a strict technical perspective, AI and machine learning offer several ways to improve network performance. ML can help improve overall network management and monitoring, efficiently increase resource consumption and enable custom network slicing to give owners more control over network usage. ML provides additional awareness of network health by providing more capabilities and features for fault, performance and security management.

ML and AI systems can identify and improve patterns of mobility and quality of service to better predict network usage and congestion at specific locations throughout the day. They can order traffic and allocate resources more efficiently, ultimately supporting better network service for users while consuming fewer resources. Advances in enterprise integration of IoT devices are helping companies control access to physical locations, monitor IT systems for intrusions and errors, and AI software that optimizes network traffic to enable edge computing and help us process information more efficiently.

The NARX-RNN technique is a good predictor of time series data because it remembers historical data and provides a more accurate estimate of future time series data. It also has the advantage over other approaches to time series prediction in that it serves to maximize the accuracy of the learning method over the training iterations. As more data is added to the model, the model becomes smarter and can better estimate traffic volumes, which is important for real-time traffic forecasting.

DNN based on LSTM for predicting time series of traffic in 5G networks. LSTM Network is an advanced RNN, a sequential network that enables information storage. It can solve the vanishing gradient problem that RNNs face. A recurrent neural network is also known as an RNN and is used for persistent memory. LSTMs have an advantage over traditional feed-forward neural networks and RNNs in many ways. This is due to their ability to selectively remember patterns over long periods of time.

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