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Article

A Survey on Routing Algorithms Based on Machine Learning

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Abstract: With the rapid development of the Internet in today's world, many computer applications have emerged, including many new network applications, such as real-time multimedia streaming services. However, traditional computer routing algorithms have defects in these emerging network applications, so we urgently need to develop new routing algorithms to compensate for them. Machine learning technology has achieved considerable results in computer vision, image generation, and game processing. In order to further improve network performance, some research groups have introduced machine learning techniques into routing problems. Unlike traditional routing algorithms, machine learning-based routing algorithms are typically driven by data. Hence, they are more adaptable to changes in network status and can make decisions promptly. Current intelligent routing algorithms demonstrate their potential through the application of machine learning, and this idea is likely to become an indispensable part of the Internet in the future. This article first introduces machine learning technology, then introduces routing algorithms using different machine learning technologies, and finally points out the development prospects of routing algorithms based on machine learning technology.

CCS CONCEPTS • Networks • Network algorithms • Data path algorithms

Keywords: machine learning; intelligent routing algorithm; deep learning; reinforcement learning; software-defined networking

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1. Introduction

The Internet has developed rapidly in recent years, and its scale has expanded rapidly. And many new applications have emerged, such as various online games, holographic communications, and industrial Internet. Various network applications have different requirements for service quality. In traditional methods, upgrading network service quality is often a simple way to expand the capacity of network equipment, which usually requires a high cost. Existing research has found that there is still much room for optimization in today's Internet . Therefore, more efficient use of network resources is a critical way to improve the quality of network services. With the growth of network scale and the increase of service types, the optimization targets of service performance have become more diverse, including delay, link bandwidth, and throughput. The delay and bandwidth in the network are dynamically changing. When the network status changes, traditional routing methods are difficult to perceive in real time and perform corresponding dynamic scheduling. Therefore, traditional routing methods limit the current computer network architecture in optimizing the above performance indicators.

Moreover, with the emergence of data center networks that can connect large-scale servers and storage devices, routing optimization, and traffic scheduling are also facing enormous challenges. Data center networks have more available bandwidth than traditional networks, but they also contain many elephant flows, making traffic scheduling more difficult. In data center networks, existing routing and traffic scheduling methods attempt to solve the optimization problems existing in the network. However, efficiently utilizing network resources is still tricky so that the effect could be better.

In the last few years, artificial intelligence has progressed rapidly and is extensively used. Significant results have been achieved in fields such as data mining and natural language processing. More and more scholars are trying to apply artificial intelligence technology to routing algorithms. Because machine learning has good expressive power, introducing machine learning into the network layer can make it more intelligent, and complex routing optimization problems can also be well solved. Compared with traditional routing methods, routing methods based on machine learning have three advantages: 1) Accuracy. We can directly use accurate data in the network when training machine learning models without the need to model complex environments. 2) Efficiency. Machine learning models can use the experience gained after training to infer input data and obtain the most valuable strategy in a shorter time. 3) Universality. In machine learning algorithms, the same model can be trained with different training data to solve different network problems. Routing algorithms based on machine learning have been well applied in many network scenarios due to the above three advantages, and they also have better scalability during deployment.

2. Machine Learning Technology

As we all know, machine learning imitates humans' thinking and learning ability in reality. It obtains experience from the data describing the problem to achieve model building and automatic analysis to solve related problems. Training a machine learning model resembles human learning, and making predictions with it mirrors human prediction processes. We can understand the machine learning method as a "black box" that can achieve our goals without caring about its internal principles. Choosing a suitable machine learning algorithm for an application in a particular field is difficult. Due to the differences in data attributes, different learning algorithms of the same type will produce different results.

Supervised learning and unsupervised learning are key learning techniques in machine learning technology. Supervised learning refers to optimizing a classifier's parameters through a set of samples with explicit attributes so that the classifier can achieve the desired performance. Supervised learning can infer a function from labeled data. In unsupervised learning algorithms, the data used is unlabeled. It can find some potential groups or models from the training data. It is fundamentally a probabilistic statistical method. The basic principle is to compress the data. Since labeled data samples are not easy to obtain, it is easy to have insufficiently labeled data samples when training the model. So, people combine supervised learning technology with unsupervised learning technology to produce a semi-supervised learning method. In semi-supervised learning, a model is trained using a limited set of hard-to-obtain labeled samples along with a larger set of easily accessible unlabeled samples. Reinforcement learning (RL) is different from the machine-mentioned learning methods. This machine learning method is a learning method for mapping environmental states to actions. Reinforcement learning does not care whether the data is labeled, but the agent continuously interacts with the environment to obtain feedback and obtain the optimal behavior strategy.

After investigation, more and more scholars have applied machine learning algorithms to routing algorithms and have shown good performance. The research on routing algorithms based on machine learning mainly includes routing algorithms based on supervised learning and routing algorithms based on reinforcement learning.

3. Routing Algorithm Based on Supervised Learning

In supervised learning, the model uses input samples and output samples with explicit attributes to learn, and the final model can accurately achieve the transformation from input data to results. Most routing algorithms based on supervised learning that have been proposed recently use deep learning (DL) technology. DL technology uses labeled samples to train the model, allowing the model to learn more complex strategies. Based on this, we can deploy intelligent routing algorithms in more complex network environments. This section provides an overview of routing algorithms that are based on supervised learning.

3.1. Routing Algorithm Based on DL

In routing algorithms based on DL, the standard routing algorithm model is shown in Figure 1. In the routing algorithm framework shown in the figure, the input data consists of real-world network topology and state information. The model uses the input data to make the routing strategy best suits the current network state.

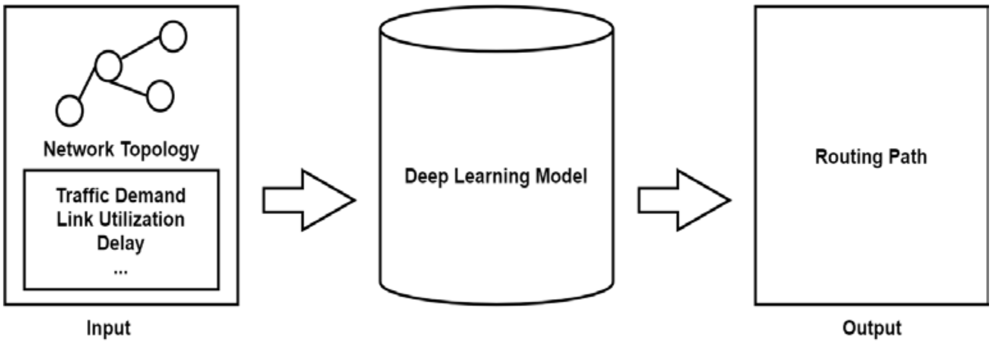

Figure 1. Routing algorithm model based on deep learning.

In recent years, SDN and NFV have developed rapidly, and service function chains (SFCs) have played an essential role in completing network services. However, the existing SFC traffic steering and routing algorithms could be better in terms of scalability, computational complexity, and efficiency. Aiming at the selection and connection problems of virtual network functions (VNFs) in SDN/NFV networks, Pei et al. [1] designed a two-stage VNF selection and connection algorithm DL-TPA. The algorithm constructs a VNF selection network and a VNF connection network based on a deep trust network to make the best VNF selection and connection solution for SFCR under high time efficiency and low computational complexity constraints. The research findings in the article indicate that the DL-TPA algorithm has high accuracy in SFCR optimal path prediction and is significantly higher than the rule-based routing algorithm regarding SFCR routing path calculation time efficiency. In the document [2], Kato et al. designed a model called TCDLS, which can be used for heterogeneous network control, introduced deep learning technology into network traffic control, and predicted single-step routing paths. The final results showed that this method was better than the OSPF routing strategy regarding signaling overhead, throughput, and delay. In the document [3], Tang et al. designed a method for learning routing paths based on abnormal traffic patterns. Mao et al. [4] designed a routing strategy called TDBA, which involves multiple parameters in network traffic. The final results showed that compared with the OSPF protocol, this approach achieved enhanced overall packet loss rates and reduced latency between nodes. In the context of a backbone network scenario, Mao et al. [5] proposed a deep learning routing strategy that can run on a GPU-accelerated Software-Defined router, effectively improving DL operation performance. The model used in this scheme is a deep trust network model. The research findings in the article indicate that this scheme has shown promising results in terms of accuracy and routing convergence speed. However, this scheme requires a high cost, and its scalability could be better.

Lee et al. [6] set connectivity as the priority of routing and designed a routing algorithm. The node degree mentioned in the algorithm refers to the node's connectivity. After evaluation by the DL algorithm, the Viterbi algorithm [7] is used to generate virtual routes, and finally, the routes are established. The algorithm of Lee et al. has better accessibility than AODV, OLSR, and ZRP routing protocols. The disadvantage of this scheme is that it needs to consider the overhead problem better, and the routing algorithm uses a centralized deep learning strategy, which is not flexible.

In contrast, the routing scheme designed by Kato [2] adopts a distributed deep-learning strategy. In this scheme, the source node trains a deep-learning model and generates a routing topology. However, in this scheme, the source node trains multiple deep-learning models, which will cause much overhead for the node. Geyer et al. [8] designed a method called GQNN in their article and added the router interface to the graph model during training. After the GNN modeling was completed, the information corresponding to the router interface included its information, the entire network topology information, and state information. Since Geyer et al. [8] also adopted a distributed routing strategy, the solution has good scalability. The research findings in the article indicate that the distributed routing algorithm based on GNN is accurate and robust.

Reference [9], Sun et al. designed a routing optimization model (DGL-Routing) based on graph convolutional neural network and Actor-Critic architecture in the SDN environment. The research findings in the article indicate that the model can better complete the routing optimization task in a complex network environment. Zhuang [10] et al. designed a GADL routing strategy. Zhuang introduced a graph-aware deep learning architecture that employs a graph kernel. The final experiment shows that the strategy not only maintains the accurate measurement of the current network status but also has a good effect in terms of efficiency.

Different applications have special requirements for specific performance, and the current routing algorithms based on DL cannot meet the different needs of next-generation network users. To resolve this issue, Rao et al. [11] proposed a constraint routing algorithm, which is a routing method that combines DL technology with the Lagrange multiplier method. This method first uses the Lagrange multiplier method to model the constraint problem in a specified form. It then maps the feature tensor to the computational space and uses it as input to train the extended short-term memory model. This model can prevent the gradient from disappearing, and the model can also capture relevant features and relationships from the input samples well. After training, the model can predict the Lagrange multiplier and then input the predicted results into the formula to calculate the objective function and obtain the optimal path. The research findings in the article indicate that the method of Rao et al. [11] has both the advantages of solving constraint problems and good learning ability so that the routing service can adapt well to complex network environments and meet the different needs of network users.

3.2. Using Auxiliary Modules to Assist in Implementing Routing Algorithms

DL methods have shown promising results in service customization, network modeling, and traffic prediction. As a result, many scholars have tried to use the results of DL technology in these areas to assist in routing calculations. In many routing optimization problems, model-based optimization methods usually use modules such as traffic prediction, congestion detection, service customization, and network modeling to assist routing calculations. Deep learning models to replace the functions of the above modules may produce better results.

In order to ensure the quality of service of IP networks, routing management systems often include prediction algorithms. In the literature [12], Barabas et al. designed an intelligent routing framework with a routing management system based on a neural network multi-task learning predictor and a situation-aware multipath routing algorithm (SAMP). SAMP performs the function of packet forwarding. The routing management system in this framework predicts the congestion of all links based on the historical data of the links. Then, it combines the prediction results with the congestion avoidance and rerouting schemes. By comparing with the OSPF and EXMO routing protocols, the final results show that this scheme can realize active routing management and improve network performance through congestion avoidance and control.

To accommodate the individualized requirements of IPv6 network users, Wang et al. [13] designed an IPv6 network service customization routing mechanism. In this mechanism, the function of the service customization module is implemented by a deep learning model called DL-SC, and the training data of this model is the service customization strategies used by users. The DL-SC model can convert user needs into specific tailored service strategies. The final results show that the routing calculation time of the mechanism designed by Wang et al. was reduced by 12.25%, the reliability was improved by 9.0%, and the service satisfaction was increased by 40.45%.

Network modeling is an indispensable part of self-driving SDN, but existing network modeling techniques must be more accurate in estimating delay and jitter results. In the literature [14], Rusek et al. designed a new GNN model that combines GNN and LSTM. In the experiment of Rusek et al. [14], the model can well learn the relationship between routing, traffic matrix and network topology and used the model to assist in routing strategy calculation. The research findings in the article indicate that the model can accurately predict the delay and jitter of the routing path in the network through input data, and the model can be applied to any topology, routing scheme, and variable traffic intensity, showing the high generalization of the model. Utilizing deep learning in network modeling enhances the accuracy and efficiency of heuristic routing algorithms, while reducing algorithmic overhead and mitigating the performance degradation caused by discrepancies between the network model and the actual environment. The method of building a deep learning model to assist routing calculation can make the routing algorithm more intelligent, thereby improving the performance of the routing algorithm.

4. Routing Algorithm Based on RL

The core of reinforcement learning (RL) includes five parts: state, agent, environment, reward value, and action. The focus of RL is how to make the agent obtain the most reward by taking a series of actions in a complex environment. As shown in Figure 2. The agent selects an action output from the action set based on the state. The action acts on the environment, and the environment enters the next state and calculates the reward value of the action. RL process is repeated continuously, and the agent gradually learns the best strategy so that its action selection in different states can bring the highest cumulative reward. This section will introduce the routing algorithm based on RL.

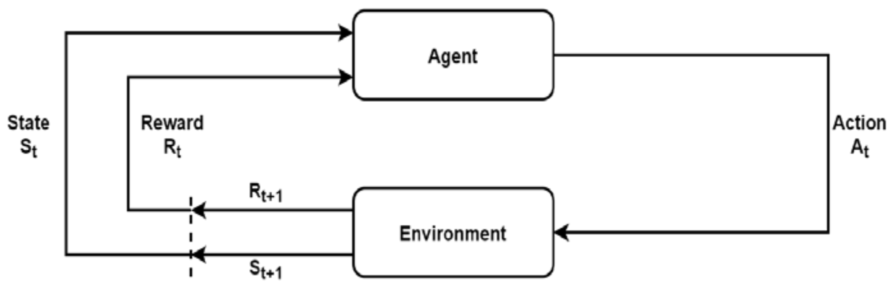

Figure 2. Interaction process between agent and environment.

4.1. Q-Learning-Based Routing Algorithm

The Q-learning algorithm is a central method in RL. Its basic idea is to learn the Q-value function Q (s, a) by taking actions and reward feedback in the environment state so that the agent can choose the most valuable action in the future. The core idea of the algorithm is to enable the agent to make the most valuable decision in the environment by learning the Q-value function.

In the document [15], Boyan first applied the Q-learning to the routing algorithm. He designed a Q-learning-based packet routing algorithm, namely Q-routing, which balances the minimization of the number of hops the packet will take and the congestion situation. The research findings in the article indicate that the algorithm can adapt well to the dynamically changing network status and quickly send data packets to the destination. Boyan's algorithm can sense the congestion in the network in a short time and adjust the routing strategy in time to avoid congestion. However, Q-routing has two defects. First, it is unable to optimize the routing strategy under minimal network load conditions, and it is difficult to sense quickly after the congestion in the network is restored. In order to solve the above problems, Choi et al. [16] designed a Q-learning-based routing algorithm, namely PQ-routing. The PQ-routing algorithm models the congestion recovery degree and the detection frequency. The final results indicate that Choi's algorithm exhibits greater stability under conditions of high network congestion.

Traditional rule-based routing algorithms cannot perform well in adaptive operations when facing dynamically changing network environments. To solve this problem, in Software-Defined Networks, Godfrey et al. [17] designed a congestion-aware routing algorithm (QCAR). In the routing protocol designed by Godfrey et al., the Q-learning algorithm is used to model the state, reward value, and Q value to find the next node, thereby finding the optimal path to the destination. The reward function designed in this experiment involves the usage of the buffer, the reliability of the link, and the number of hops. The research findings in the article indicate that compared with the existing solutions, the end-to-end delay of this scheme is shortened by 15%, and the packet delivery rate is increased by 20%, which improves the overall performance of the network.

Similarly, for traditional routing protocols that make routing decisions using only limited network information, it is difficult to adapt to traffic mutations that affect network performance. Casas-Velasco et al. [18] designed a routing algorithm RSIR in the SDN architecture. The algorithm integrates the learning capability of reinforcement learning with the global view and control provided by software-defined networks. In addition, the RSIR algorithm pays attention to the state information of the link when making routing decisions. This consideration enables the RSIR algorithm to learn and utilize potential routing paths well in dynamic network environments. The research findings in the article indicate that compared with the Dijkstra algorithm, the RSIR algorithm has better scalability, datagram loss, and delay results.

4.2. Routing Algorithm Based on DRL

Deep reinforcement learning (DRL) integrates DL with RL techniques, employing neural networks to estimate the Q function, enabling intelligent agents to learn better in high-dimensional space. Deep Q-learning (DQN) is a classic deep reinforcement learning method. In the past few years, DRL technology has been well-developed and has achieved considerable results in many fields. Therefore, many scholars have applied deep reinforcement learning technology to routing algorithms to handle complex routing problems better.

In the literature [19], Swain et al. applied DRL to the SDN routing optimization algorithm. They designed a model called CoDRL, which combines deep deterministic policy gradients with convolutional layers to minimize the average network delay and congestion. The final experiment shows that compared with the traditional static routing algorithm, the CoDRL model performs better regarding delay. In the literature [20], to solve the problem, the existing routing algorithm cannot promptly make the most effective routing decisions in a dynamic network environment, thereby reducing the network transmission performance. Rao et al. designed an adaptive routing algorithm (DAR-DRL). The algorithm combines the link-aware graph learning model with the reinforcement learning algorithm, which can not only adaptively avoid loopholes and loops in the network but also improve the robustness of the routing algorithm. The final experiment shows that the DAR-DRL method outperforms traditional routing methods in network transmission performance, such as throughput. In the literature [21], Cong et al. designed a centralized and distributed efficient routing scheme (RLR-T) to meet the requirements of network applications for network latency and accuracy.

In order to optimize multipath routing, Zhang et al. [22] introduced a TBPPO algorithm for SDN. The algorithm takes into account the overall network security, delay, and fluctuations in multipath delay. The final experiment shows that this algorithm reduces the average delay by 20% compared with the traditional routing method, and SDN's overall security and routing efficiency are also improved. In the reference [23], Chen et al. combined proximal policy optimization with pre-convergent actor-critic network technology to design the FCACN model and improved the delay-sensitive routing algorithm. The routing algorithm proposed by Chen et al. can meet the requirements of delay-sensitive applications and complete routing tasks in complex environments. In the reference [24], Kim et al. developed an M/M/1/K queue-based model and used this model to improve the DRL routing algorithm. The algorithm trains a deep reinforcement learning agent and determines a set of optimal link weights by the agent. The purpose is to reduce the network's packet loss rate and delay and use the aggregated traffic matrix as the agent's input to improve network routing performance.

In the literature [25], Casas-Velasco et al. designed a DRSIR routing algorithm, which overcomes the problem that the learning process of the reinforcement learning-based routing algorithm is too complicated when dealing with significant action and state spaces. The research findings in the article indicate that the DRSIR algorithm is superior to the traditional Dijkstra algorithm in terms of scalability, packet loss, and delay. In the literature [26], Liu et al. designed a DRL-R algorithm, which solves the problem that the traditional routing algorithm cannot make up for the gap between the performance demands and resource distribution of different flows in the network. In the literature [27], Zhao et al. designed a GDQR routing algorithm, which designed the reward function of the routing algorithm. Based on the Markov decision process, the decision and training parts of the routing algorithm were proposed, and finally, the model was trained. The results show that the GDQR algorithm can adapt well to the dynamic network environment and adjust the routing in time. In addition, the algorithm can be used directly in similar environments without repeated training. In the document [28], Zhao et al. proposed a multicast routing algorithm DRL-M4MR, aiming to solve the problem that the existing multicast routing methods cannot adapt well to the dynamic network environment and have low data forwarding efficiency when constructing multicast trees. The algorithm uses the ability of software-defined networks to perceive the global network to design the state space of the multicast tree, making good use of the state information in the network. The DRL-M4MR algorithm also uses technologies such as dual network structure, dual network structure, and priority experience replay, which shorten the convergence time of the intelligent agent. The research findings in the article indicate that compared with the KMB algorithm, the algorithm can construct a better multicast tree path, adapt well to complex network environments, and flexibly forward data.

5. Summary and Outlook

With the rapid advancement of the Internet and the ongoing expansion of network scale, users have higher and higher requirements for the quality of network services, and traditional routing algorithms are complex to meet people's needs. Machine learning technology has achieved considerable results in natural language processing and image recognition. Therefore, many researchers have integrated machine learning technology into routing algorithms and achieved specific results. Compared with traditional routing algorithms, routing algorithms based on machine learning technology can better adapt to complex and changeable network environments. Machine learning-based routing algorithms have demonstrated significant potential. In the future, by utilizing machine learning technology, network routing algorithms will become more and more efficient and intelligent. Routing algorithms have broad development prospects.

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