Automatic Generation of Urban Road Planning Network Under Deep Learning

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Abstract. With the rapid advancement of China's urbanization process and the rapid increase of the number of motor vehicles, now the vast majority of cities in China are faced with traffic congestion, environmental pollution, noise pollution and other problems. Facing these problems, a road network with reasonable structure, proper layout and sufficient capacity has become an important basic condition for the sustainable development of urban traffic system. This paper mainly studies the automatic generation method of urban road planning network based on deep learning. In this paper, a model based on deep neural network is proposed, which integrates the knowledge of road planning domain and generative adversarial network, and can realize the generation of road network simply and quickly.

Key words: Deep Learning, Urban Roads, Road Planning, Adversarial Networks

1. Introduction
As an important subsystem of urban large system, urban traffic system is open and complex, consisting of three parts: urban road network system (the channel of traffic behavior), urban transport system (the operation of traffic behavior) and urban traffic management system (the control of traffic behavior) [1]. Urban road network is a network structure of roads crisscrossed by urban roads. Its basic elements are road sections and intersections. The urban road network system is the important foundation of the urban traffic system and the external skeleton of a city. The determination of the skeleton of the road network determines the outline and potential of the urban development to a great extent. The reasonable layout, clear hierarchy and appropriate scale of a city's road network directly affect the normal operation of the entire city's economic development, social life and other functions, and have far-reaching influence on the development of a city [2]. However, we must clearly realize that the urban road network is a typical, open and complex giant system. The openness of the system is reflected in the fact that the road network exchanges material, energy, information and other factors with the outside world while developing itself. The complexity of the system is reflected in many aspects: from the perspective of the macro scale of the road network, the urban road network contains a large number of road sections and intersections, and the layout of the road is different, and different intersections will produce intersections of different shapes [3]. Deep learning is the most concerned research hotspot in the field of computer at present. It is of great significance to introduce the latest research results of deep learning into the field of urban planning to solve the problems of urban road
network planning.

Currently, road network planning methods are generally divided into three categories: model-based road detection methods, feature-based road detection methods and machine learning-based road detection methods. The core of model-based road planning method is to establish a mathematical model for road identification [4-5]. At the beginning of the study, researchers established mathematical models by analyzing the geometric shape of roads. At first, straight-line models were used. However, in reality, there were a large number of non-standardized roads, uneven and discontinuous road edges, and straight-line models were only used for roads with relatively standard structures. In real roads, shadows, occlusion, uneven road edges and non-connection have a great impact on the accuracy of road detection [6].

The core content of this paper is to introduce deep learning technology into the field of urban planning, to solve the problem of automatic modeling of urban road network, and to provide a new idea for urban road planning. Specifically, this paper constructs a deep nonlinear road network generation model, which can learn the characteristics that characterize the nature of data, and on this basis, can generate a road network system with a strong sense of reality and similar to the distribution of training samples.

2. Urban Network under Deep Learning

2.1. Structural Characteristics of Urban Road Network

Road network is the most important external form of urban network materialization, the framework of urban organization of various functional land, and the carrier of urban social production and residents' living activities. The formation of urban road network will be affected by local political, economic, cultural and other social factors, as well as various complex factors such as natural geographical environmental conditions, modes of transportation and requirements of the overall urban layout [7-8]. Therefore, the structure of urban road network does not have a unified and fixed form. In the established urban road system, the road network model can be divided into the following four types [9].

(1) Square road network

Square or checkerboard road network is the most common type of road network. The topology of the road network is mostly rectangular or square. The main roads are set every certain length, with the same direction and parallel to each other. The distance between the main roads is usually about 1000 meters. The layout of secondary main roads is carried out in the area surrounded by the main roads, and the urban land is divided into blocks of appropriate scale. The layout pattern of square road network is very suitable for cities with flat terrain. The square road network has the following remarkable advantages: the overall layout of the road network is neat, the traffic flow on the road network is evenly distributed, the capacity of the road network is used in a balanced way, and there is no overloaded traffic pressure in the city center; this kind of road network will not form complex intersections, most of which are cross-shaped or T-shaped intersections, and the traffic organization at the intersections is simple and convenient. Because this kind of road network is composed of several parallel roads, it has great flexibility in redistribution of traffic flow. When a certain road in the road network is blocked, the road direction identification is good, and the vehicle can choose many detour routes, but the vehicle traveling time remains the same.

(2) Ring radial road network

Circular radial road network is a kind of urban road network form formed by the long-term development of a city center. It originates from the planning idea of organizing cities by squares in Europe. It is the product of geometric composition at first, and is mostly used in big cities.

Circular radial road network has the advantage of smaller non-linear coefficient, which facilitates the traffic connection between the city center and each functional area as well as between the urban
area and the effective area. Radiative ring road network is very beneficial to the balanced distribution of urban traffic volume, and has strong ability of traffic evacuation, which can avoid excessive traffic pressure in the city center. However, the disadvantages of the circular radial road network are also very significant. The downtown area of this kind of road network is very easy to attract the traffic flow from the periphery of the city, resulting in the shortage of traffic resources in the downtown area. Compared with the square road network, the traffic mobility is worse, and it is easy to form irregular blocks, which is not conducive to the layout of buildings.

(3) Freestyle Road Network
Freestyle road network is usually a kind of irregular road network form combined with undulating terrain and complex landform. This type of road network has no fixed shape and varies greatly. The important advantage of the freestyle road network is that it makes full use of the natural terrain features and geographical conditions to layout the road and saves the cost of road investment. However, the disadvantages of freestyle road network are also very significant: the road route is curved, the non-linear coefficient is large, and it is not suitable to identify the direction; the uneven distribution of line density greatly increases the difficulty of traffic organization and management. In addition, the lines of freestyle road network are relatively fixed, which is not conducive to the later transformation and upgrading. Freestyle road network is suitable for cities with complex terrain conditions, and some cities in mountainous and hilly areas often adopt this model.

(4) Mixed road network
The combined road network is a comprehensive road network, which combines the road systems of different functional areas closely according to the geographical conditions of the city, such as the actual terrain, landform and the demand of urban traffic. Because of the integration of several basic types of road network, the road network can meet the basic traffic needs as well as the economic and architectural needs. The mixed road network takes the natural and historical conditions into full consideration, which is conducive to the organization of traffic according to local conditions, and gives full play to the advantages of several road networks, so that the urban road system can be planned and developed in a complete and unified way. The disadvantage is that the non-linear coefficient is large, the irregular blocks are many, and the building land is scattered.

2.2. Automatic Generation Model of Urban Road Network
Compared with text data, images, audio, video and other types of data can express more abundant information, and the data distribution they obey is more complex. Building a generative model that can learn these complex data distributions has always been a challenge in the field of machine learning. Some deep generative models, such as deep Boltzmann machine, deep belief network and restricted Boltzmannization, have not been proposed until recent years. These models are mainly based on the Markov Chain Monte Carlo (MCMC) method to calculate the gradient of the logarithmic likelihood function. However, the gradient becomes more and more inaccurate with the training process, mainly because the samples of the Markov Chain cannot be quickly mixed with different models. Recently, the generative model has gained new development. Some scholars proposed a generative model based on back propagation training to avoid the problems encountered in MCMC training. The most representative one is the generative discriminant network, which uses the idea of adversarial training and directly displays the data distribution of the network output through back propagation.

In this paper, a road network generation model is constructed based on generative adversarial network and automatic coding machine. The model consists of three subnetworks. The first part is the road network coding network, which is used to convert the road network data into the road network coding. The second part is the road network decoding network, which decodes the road network code into the road network data again. The third part is the road network discriminant network, which is used to judge whether the distribution of input codes is the same as that of road network codes.
Among them, the first part and the second part constitute an automatic encoding machine, and the first part and the third part constitute a generative adversarial network [10-11].

In this paper, a fully connected neural network containing a hidden layer is used to implement the coding network of the road network. Layer1 is used as the input layer to receive the road network data participating in the training. The setting of the number of neurons needs to be consistent with the dimension of the road network data. Layer2. Layer2 is the hidden layer. Generally, there is no fixed limit on the number of neurons in the hidden layer, but there is an empirical formula for reference:

\[ n_{\text{hid}} = \sqrt{n_{\text{in}} + n_{\text{out}}} + \sigma \]  

(1)

Where, and Nin and Nout represent the number of neurons in the input layer and the output layer respectively, and \( \sigma \) is the regulation constant. The activation function used in the hidden layer is a nonlinear ReLU function, because from a biological perspective, ReLU is closer to the activation model of brain neurons [12]. Layer4 is the output layer, which outputs a binary road network code (X, Y). All layers are connected with each other in the way of W full connection, which realizes the coding of road network data together. Road network coding is subject to distribution of \( q(z) \), \( z \sim q(z | x) \). Among them

\[ q(x) = \int q(z|x)P_d(x)dx \]  

(2)

Similar to the coding network, we use a four-layer fully connected neural network to realize the decoding network of the road network. Layer1 is the input layer to receive the input road network code. The number of neurons needs to remain the same as the dimension of the road network code. The hidden layer of Layer2 and Layer3 has no fixed limit on the number of neurons, and the activation function uses the ReLU function. Layer4 is the output layer, which outputs the road network data reconstructed by decoding. The number of neurons needs to be consistent with the dimension of the road network data, because only in this way can we ensure that the road network coding can be restored to the road network again. The activation function used by Layer4 is the tanh function, which maps the output to the interval.

3. Model Training

3.1. Experimental Data
The model training data in this paper are collected from the web crawler network, which covers the road network information of 30 large and medium-sized cities in China. After screening, the sample size reaches 10,000, which can meet the basic demand of the road network generation model for the amount of training data.

3.2. Experimental Platform
The local computer is equipped with an NVIDIA RTX 2060 graphics card, and the operating system is Ubuntu 14.04LTS desktop operating system. Limited by the hardware level, the model training time is long. The rented cloud server is loaded with a Kepler-based Nvidia Tesla K80 server graphics card. Cloud server has obvious advantages in hardware configuration, which is more in line with the hardware requirements of this experiment. For laboratories with conditions, it is recommended to use the cloud computing platform (or purchase a professional-grade graphics card) to perform model training; Otherwise, you can choose to deploy the training environment on your own machine.

3.3. Model Training Process
After setting up the environment, you can start the training of the model. In this experiment, the model uses the stochastic gradient descent method (the automatic encoder and generative adountational network are trained alternately, where the learning rate is 0.001, the weight attenuation is 0, and the momentum factor is 0.5. Each time, 200 samples are randomly selected from the training set to participate in the training process. Use random numbers that obey uniform distribution; Initialize the network weights. The maximum number of training rounds of the model is set as 1000 rounds, network parameters are updated 5000 times in each round, and the loss function of each network is
calculated after each round.

4. Model Training Results

4.1. Road Network Classification Accuracy

Table 1. Classification accuracy of road network

| Model   | IoU/%   | PA/%   |
|---------|---------|--------|
| FCN     | 57.93%  | 90.82% |
| U-net   | 64.72%  | 92.98% |
| deeplab | 62.41%  | 92.57% |
| Proposed| 68.07%  | 93.82% |

![Figure 1](image.png)

Figure 1. Classification accuracy of road network

As shown in Table 1 and Figure 1, the method proposed in this paper has the highest IOU detection accuracy and the highest PA detection accuracy. Compared with the detection accuracy of FCN (57.93%), the accuracy of our method IOU is 10% higher and 6% higher than that of DEEPLAB. This proves that the model proposed in this paper has higher performance in road classification detection.

4.2. Specific Type of Road Network Generation
Figure 2. Generating scores for a specific type of road network

As shown in Figure 2, from the perspective of the quality of generated road network, the new sample not as clear and sharp as the training sample, there is a blur and noise, the problem in the image generated by the related research is still not very good solve the problem, especially for large size sample images, reconstruction difficulty bigger, moreover applying PCA feature dimension reduction can also lead to loss of information. From the content of the sample, the form of the road network is obvious, and the distribution of the road network is basically reasonable. The shape of each type of road network basically conforms to the characteristics of this category, which can be summarized as follows: the road network with high density is obviously denser; the regions with high economic index have a larger proportion of trunk roads and a higher density, which is consistent with our common knowledge of road network.

5. Conclusions

Based on the analysis of the characteristics of urban road network and the external environment, the factors influencing the evolution of urban road network mainly include traffic demand, road travel supply, geographical restrictions and the internal optimization of the evolution of urban road network. A deep road network generation model is established. Based on the training of massive road network samples, the model learns the rules and characteristics of road network gradually in the training process, and then realizes the understanding of road network. After the training, the model can generate a large number of road networks of the specified type in a short time. One of the advantages of this approach is that the model only needs to be trained once and then can be used in any scenario. This paper also integrates the principle of road network planning into the training of the model, which is easy to be ignored in the research of W. Adding the planning principle can make the model understand the road network samples from a more scientific perspective, and the knowledge learned is more in line with people's understanding of the road network.

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