Research on Edge Network Topology Optimization Based on Machine Learning

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***Abstract*—Edge network topology optimization is an innovative structural design method that has made significant breakthroughs in the fields of aerospace and engineering. The use of data-driven network topology optimization has become the direction and trend of future structured topology research. At present, machine learning is fast, with greatly improved efficiency and accuracy; Machine learning can effectively solve the time-consuming problem of traditional implicit topology; And the prediction result of machine learning algorithm can be used as the Initial condition for optimizing the movable deformation component, so as to achieve the effect of rapid convergence. Network structure topology optimization can be widely applied in the field of science and technology, deepening scientific research, and promoting the continuous development of scientific productivity.**

Keywords-data-driven; Machine learning; Edge network; Network structure; algorithm

I. INTRODUCTION

People have been looking for innovative design to improve production efficiency. In modern society, efficient design methods are still a promising prospect.It has been the design goal of structural designers to meet the requirements of serviceability with the least material (cost).[1] The traditional method is to make a variety of initial designs based on experience and intuition, then calculate and analyze each scheme, and determine the final scheme according to the results. This method has obvious limitations.

First, the quality of the initial solution depends heavily on the level of the designer. Second, the whole process takes a lot of time and labor costs, and the optimal solution may not exist in the set of initial solutions.[2] In view of the shortcomings of the traditional methods, domestic and foreign scholars began to try to find a method that can automatically find the optimal design scheme based on the given design objective. With the improvement of computer performance and the in-depth study of optimization theory in the field of mathematics in recent years, structural topology optimization technology has developed rapidly, and has been widely used in civil, automotive, mechanical and other fields.

II. BASIC THEORIES AND METHODS OF MACHINE LEARNING

A. Machine learning model

Machine learning is an important method to realize artificial intelligence. Its core task is to design a reasonable model first, and then let it learn historical data and experience, so as to complete specific target tasks. Different from the traditional expert system, the advantage of machine learning lies in its learning ability.If the model fails to fully learn the knowledge carried by the historical data, it is called model underfitting; conversely, if the model overlearns the noise information in the historical data, it is called model overfitting.[3]

Machine learning models can be classified into traditional machine learning models and advanced machine learning models according to their development process. According to different training methods, traditional machine learning models can be divided into supervised learning, semi-supervised training learning and unsupervised training learning models. [4] The core difference between supervised and unsupervised learning is whether the training data is artificially labeled.The training mode of supervised learning is to label the training samples first, and then let the model learn the mapping relationship between the features of the data and the labels. Typical supervised learning models include classification algorithms such as artificial neural networks, support vector machines, decision trees, and Bayesian classifiers, and regression algorithms such as linear regression, L1 regularized regression, L2 regularized regression, and least squares.The training mode of unsupervised learning is to let the model directly learn the characteristics of the samples, and then distinguish the samples according to the different characteristics of the samples. [5] Typical unsupervised learning models include K-means, QT clustering, principal component analysis, SVD, singular value decomposition of matrix, self-encoder and other dimension reduction algorithms.Semi-supervised learning is between supervised learning and unsupervised learning, which lets the model learn knowledge from a mixture of labeled and unlabeled data samples.Typical semi-supervised learning includes generative models, semi-supervised support vector machines, self-training algorithms and other generative algorithms. Advanced machine learning models include deep learning, reinforcement learning, transfer learning, etc. Deep learning models mainly include deep neural networks, convolutional neural networks, recurrent neural networks and self-coding

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neural networks.Reinforcement learning mainly includes Q-Learning, Double Q-Learning and other models. Transfer learning includes spectral analysis, self-learning, TPLSA and other models. The classification diagram of the machine learning model is shown in the following figure.As shown in Figure 1.

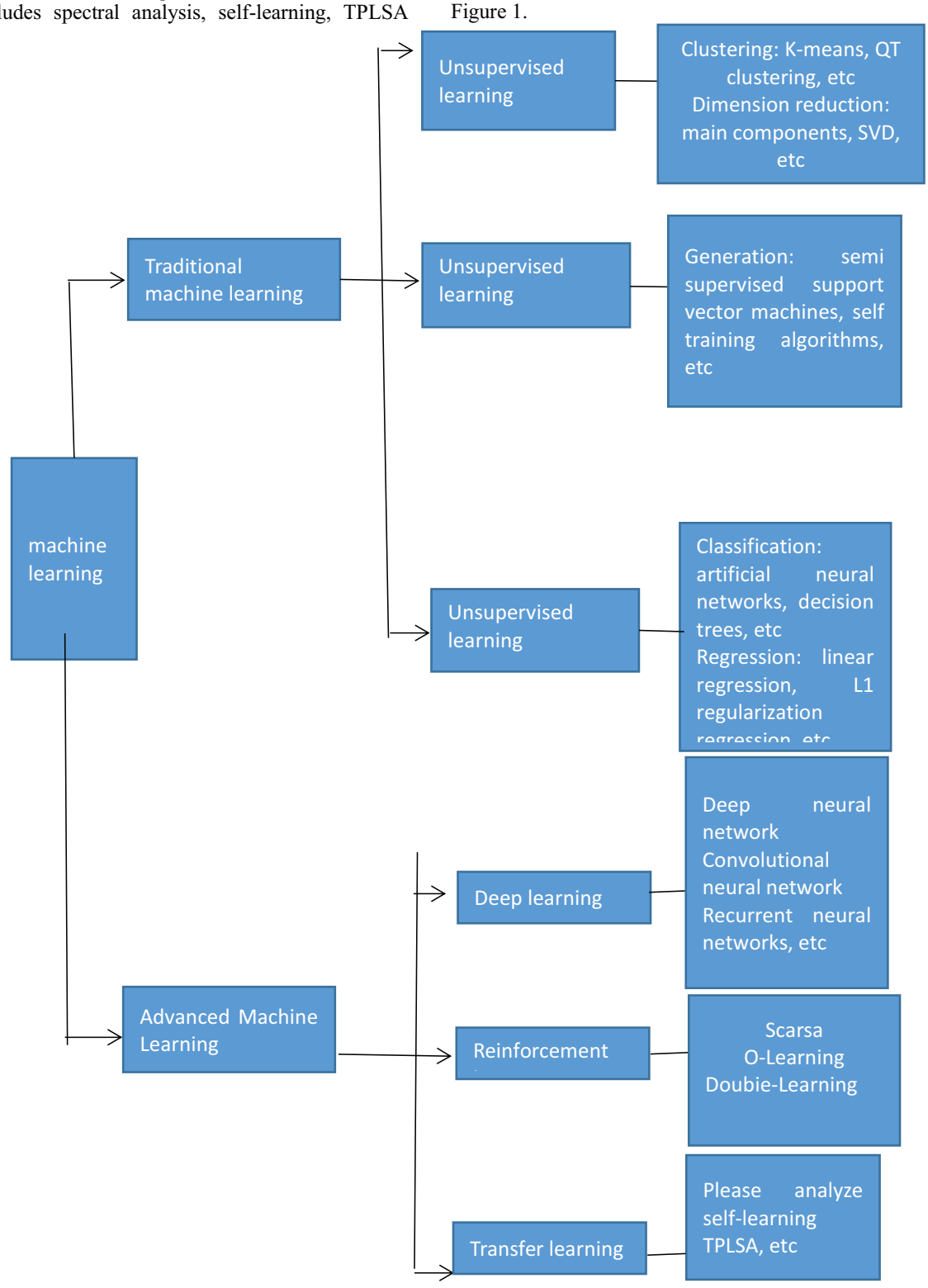

Figure 1. Classification of machine learning models

B. Deep learning model

Artificial Neural Network (ANN) is a mathematical model that mimics the biological nervous system. An ANN consists of a large number of neurons, each of which is a nonlinear activation function that mimics the response of a nerve cell to the environment. The interconnection of neurons mimics the transmission of biological neural signals.The simplest ANN model is a simple network model which only contains an input layer, a hidden layer and an output layer. Each layer of the network is composed of a number of neurons. Neurons use sigmoid activation functions to simulate the response of human brain cells to stimuli.ANN has certain learning ability and fault-tolerant ability, and can realize classification, regression, dimensionality reduction and other functions, which belongs to a powerful machine learning model.

Artificial Neural Network (ANN) is a mathematical model that mimics the biological nervous system. A neural network is composed of many neurons, each of which is a nonlinear activation function. The interconnection between neurons is a process similar to the transmission of biological neural information. The simplest artificial neural network model is a simple neural network model that only contains input layers, hidden layers, and output layers. There are many neurons at each level. Neurons use an S-shaped activation function to mimic the activity of the brain under external stimuli. NN has certain learning and fault tolerance capabilities, and can achieve various functions such as classification, regression, dimensionality reduction, etc. It is a very powerful machine learning model.[6]

The essence of ANN learning is to fit the nonlinear mapping relationship from the input to the output of the model, and the representative of the traditional ANN model is Back Propagation Neural Network (BPNN). The BP neural network revises the connection weights between neurons by reversely transmitting the difference between the model output value and the true value, so as to realize the fitting from input to output.BP neural network is a shallow neural network, which generally contains only two layers, namely, the input layer, the hidden layer and the output layer.Shallow neural network has some disadvantages, which are mainly manifested in its lack of ability to fit complex high-dimensional functions.[7] The features of samples need to be defined, and the dimensions of features are related to the number of neurons in the input layer of the model, so the generalization ability of the model is insufficient. There is no information sharing mechanism between neurons, only the one-way transmission mechanism of information.

Deep learning (DLs) originates from artificial neural networks, and its essence is to optimize the multi-level neural networks of artificial neural networks. Compared to shallow neural networks, deep neural networks have a more intuitive performance, implying more hidden layers; From the perspective of biomimetic mechanism, deep neural networks are closer to more complex organisms. In terms of perception and learning of the environment, deep neural networks are superior to shallow neural networks. However, the working mechanism of deep neural networks is more complex, and the required computer simulation process is also more complex. Simply increasing the level of the BP neural network will result in poor fitting and convergence of the network. This is because during reverse transmission, the error of the product of each layer increases or decreases with the increase of the number of layers, which cannot effectively adjust the connectivity weights between each layer. So, in order to prevent deep neural networks from falling into local optima and even not being able to train, it is necessary to design appropriate network structures based on specific problem scenarios[8].

III. Traditional structural topology optimization method

A. Variable density method

SIMP method is the most widely used algorithm in commercial software at present, which is widely used in commercial finite element software such as ABAQUS of Dassault SIMULIA, Optistruct of Altair and ANSYS.In addition to the finite element element change from zero to one, the SIMP method also introduces many numerical techniques. The main idea is to divide the design domain into many finite element elements. [9] The material filling rate p (X) of the finite element in the structure changes from zero to one, expecting to get a non-zero or one result in the end, and then get the optimal material layout in the design space.The SIMP method has been questioned because of its inability to reasonably explain the physical properties of materials that exist in nature. In 1999, Bendse and Sigmund [7] first introduced the concept of penalty factor. As long as the penalty coefficient and Poisson's ratio satisfy the condition (V = 1/3, p23), this method can describe the physical properties of materials.In order to remove the transition element and get the 0-1structure, it is often achieved by setting the filter radius. In 2007, Sigmund 8 introduced a modified SIMP penalty model, which can filter the solid element. The idea is as follows:

$$\boldsymbol{E_{a+2}(x) = E_{\min} + \rho(x)^a \left(E^0_{aji} - E_{\min} \right), p \geq 3}$$

$$\boldsymbol{\int_D \rho(x) d\Omega \leq \bar{V}; 0 \leq \rho(x) \leq 1, x \in \Omega}$$

E^0_{ijkl} Is the elastic modulus of the solid material, is a positive decimal, represents the elastic modulus of the empty material, can avoid the singularity of the single stiffness matrix, and p (X) represents the density function of the element material. The SIMP method can optimize the design area of arbitrary shape, and is suitable for stiffness, multi-case, multi-load, multi-material and other problems.E_{min}

B. *Progressive structure method*

Evolutionary structural optimization (Evolutionary Structural Optimization method, ESO) was introduced by foreign scholars Xie and Steven. Evolutionary structural optimization (ESO) discretizes the initial design domain into many finite elements, and the solution of structural topology optimization problem is actually to find a subset of finite elements.In order to obtain a clear and optimal topology, more finite elements need to be divided, which greatly increases the computational cost. [10] Compared with the SIMP method and the level set method, the evolutionary structural optimization method does not need to analyze the sensitivity of the structure, but the calculation time is much more than the above two methods.Although evolutionary structural optimization is widely used in machining, bridge design, civil engineering and other fields, the further development of evolutionary structural optimization is limited because of its low efficiency and poor convergence when dealing with large-scale problems.As shown in Figure 2

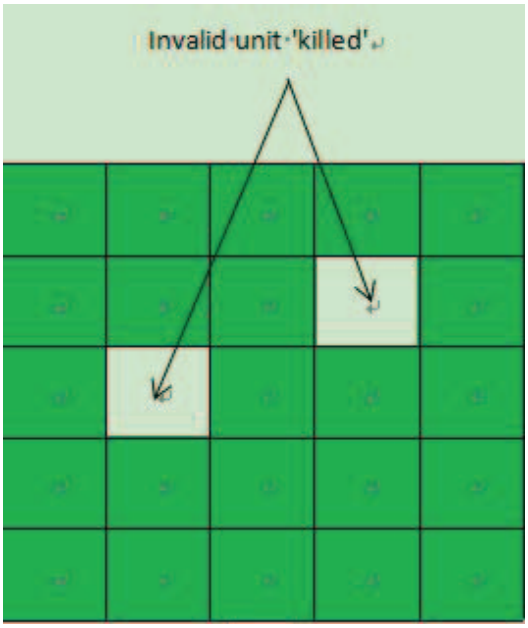

Figure 2. Material model described by ESO method

IV. Machine Learning and Structural Topology Optimization

Roughly speaking, machine learning can be divided into four categories: supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning. In supervised learning, the data consists of input X and output y.Unsupervised learning, only input X, no label y, given a pile of data, to find out whether there is a clustering effect between the pile of data, can be divided into several groups, mining out the structure behind the data. In unsupervised learning, it is hoped that the machine can learn to learn the hidden patterns in the data without labels.Between supervised learning and unsupervised learning is semi-supervised learning. Semi-supervised learning is the most important kind of learning that meets the actual needs. Only a part of the data has labels. Reinforcement learning has been developing rapidly recently, and AlphaGo's success lies in reinforcement learning. Supervised learning is used in this paper.

Generally speaking, machine learning consists of three parts: data representation, optimization and evaluation. Before doing supervised learning, there is a very important assumption: all data samples are generated from an unknown and fixed probability distribution, hoping to find a rule that can correctly classify its label.If it is inconsistent, it will be punished. For a rule, at least it should perform well on the training set. This is the basic idea. For example, to classify cars, we need a way to express the concept of cars. To describe a car, we can use two attributes: the price of the car and the size of the engine. We can define different characteristics to describe a car.

Most machine learning algorithms can be described as an optimization problem, that is, to find the minimum value of the loss function. Loss function is used to measure whether the function in the function set achieves the best, hoping that the training error is as small as possible, that is, the performance of the model on the training set is good, which is generally called bias.At the same time, the complexity of the model should be reduced, which is called variance. By controlling the complexity of the model, the problem of over-fitting can be avoided. In the era of big data, we often encounter massive amounts of data, and the generation of data is very fast. Online learning and random optimization techniques may be a good solution.

The framework of machine learning can be roughly divided into three steps, the first is to determine a set of functions, the second is to let the machine measure the quality of a function, and the third is to let the machine have an automatic good algorithm to pick out the best function. These three steps of machine learning simplify the process of machine learning, just like putting an elephant into a refrigerator.

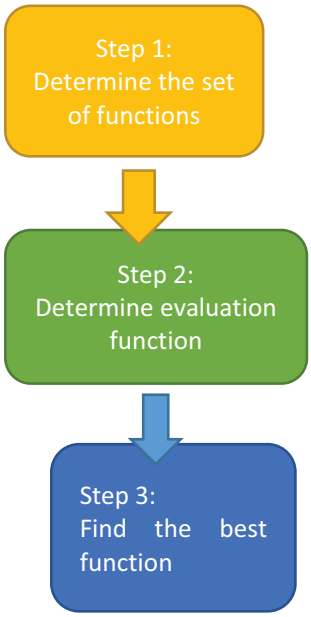

Figure 3. Machine learning framework

In machine learning engineering applications, the collected samples often contain a large number of features, and there is often a certain degree of correlation between the features. If we do not take dimension reduction measures, we will get poor quality data. A large number of features will increase the complexity of machine learning algorithm, and even make it difficult to train.At the same time, the large number of features will lead to the disaster of dimensionality, which will reduce the prediction accuracy of machine learning model. Feature selection can eliminate irrelevant or redundant features, thus reducing the number of features, reducing the complexity of machine learning algorithm, and improving the prediction performance of the algorithm. On the other hand, selecting the relevant features can simplify the model.

Research on Structural Topology Optimization Based on Artificial Feature Extraction

A. Introduction to Removable Deformation Components

Moving Morphable Components (MMC) is a structural topology optimization method based on Moving Morphable Components proposed by Professor Guo Xu [25] in 2014, which has been highly concerned and recognized by international peers.The basic idea is to arrange a number of components in the whole design area, and the boundary of each component describes its shape through control points. Driven by the optimization algorithm, these components move and deform in the design area, and finally get the topology of the structure. This algorithm can realize the integrated design of the shape, size and topology of the structure.

B. Machine Learning Framework Based on Movable Deformable Components

1) Basic idea

The application of artificial intelligence and machine learning is not limited to Go. Machine learning has gradually changed human life in the fields of face recognition, unmanned driving, machine translation, medical diagnosis and so on.

At present, the method of machine learning is advancing rapidly, which has innovated the traditional research mode. The difference between classical methods and machine learning methods in solving practical engineering problems is that classical methods first do experiments, through experimental observation, collect data, summarize statistical rules and then piece together empirical formulas.After that, some assumptions are put forward, idealized models are introduced, mathematical models are established based on a certain law in physics or a certain theorem in geometry, differential equations satisfied by the problem are listed, and natural laws are expressed by differential equations. Then the numerical simulation is carried out to optimize the prediction. Finally, the prediction is verified by experiments.When using machine learning methods to deal with practical problems, the first step is consistent with the classical method. First, we need to accumulate data through experimental observation, then select a machine learning algorithm, and use these data to train, which may involve a complex process of parameter adjustment. Finally, the model is trained and used to predict.

In this paper, a data set is generated by using the method of movable deformable components, and a machine learning algorithm is trained by using the data set.As shown in Figure 4The ultimate goal is to predict the design variables of the components in the structure as soon as the boundary conditions of force and displacement are given, and then to obtain the optimal topology structure, that is, to realize the real-time topology optimization design of the structure.

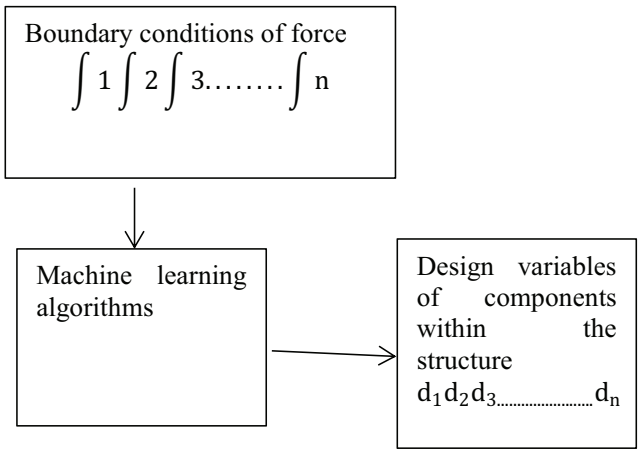

Figure 4. Structural topology optimization under machine learning framework

2) Machine Learning Algorithms

Machine learning is one of the most exciting technologies at present. KNN is a lazy learning method, which can be directly used to predict without learning a machine learning model.KNN is also known as instance-based learning. Mencius' mother moved three times. Those who are close to the ink are red, and those who are close to the ink are black. KNN is based on a similar concept. Its basic assumption is that if two samples are very close, they should also have the same label. KNN, also known as memory-based learning, is to memorize all the samples in the training set.For a new sample, look for its K neighbors, that is, find out the K samples closest to it, and then do a majority vote to count which label occupies the vast majority, to determine which label it should belong to. Because these K samples come from the training set and have corresponding labels, look at these K labels and do majority voting to determine the label of this sample.KNN adopts a democratic mechanism, and generally K often chooses odd numbers to avoid the situation of equal scores. The smaller K is, the more complex the model is, the easier it is to overfit, and the more complex the decision boundary is. Usually, the process of adjusting parameters is needed to determine the best parameter K.The larger K is, the more concise the model looks and the clearer the decision boundary is, but the larger K is, the more accurate the prediction can not be made. Complex models sometimes have the risk of overfitting. The distribution of data is not so easy. The accuracy of simplified models is not good enough. K = 1 is often overfitting.

The use of KNN algorithm will involve the concept of distance, in the KNN algorithm, the selection of different distance functions will lead to different results, if all the features are real-valued, the distance function can use Euclidean distance, if the features are discrete, Hamming distance is often used, that is, the same distance is one, different distances are zero. There are different ways to calculate the length.

V. CONCLUSION

Based on the network topology of machine learning model, this paper proposes the optimization method of network topology based on data-driven, combined with the given convenience and conditions, for the marginalized network structure, based on data-driven to build the optimized topology, give full play to the advantages of machine learning prediction and matrix operation, optimize the network topology, I believe that in the near future,The network edge structure under the machine learning algorithm will be more optimized, and the related functions will be more sound.

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