CHAPTER VII

NEURAL NETWORKS: OVERVIEW AND SPACE DEBRIS APPLICATION

REDES NEURAIS: OVERVIEW E APLICAÇÃO À DETRITOS ESPACIAIS

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ABSTRACT

Artificial neural networks (ANNs) are tools in the field of artificial intelligence (AI) whose structure and working process are based on the human brain. ANNs are used for solving decision-making problems and pattern identification, and they are particularly useful for solving non-linear problems with a large dataset whose internal mechanisms aren't well understood. ANNs stand out from conventional methods due to their high capacity for modeling complex non-linear systems from a dataset, their superior performance in most applications, their adaptability, and their capacity for processing a large amount of information. However, the application of ANNs also presents some difficulties, such as a high computational burden, the necessity of a large dataset to operate well, their Black Box nature, and the lack of standardization. Nowadays, a prominent application of ANNs is in the detection of satellite and space debris streaks in astronomical images, which can be used to identify objects in orbit, non-cataloged debris, and to better understand the orbital environment.

Keywords: AI. ANNs. Brain. Adaptability. Debris.

RESUMO

Redes neurais artificiais (ANNs) são ferramentas no ramo da inteligência artificial (AI) cuja estrutura e funcionamento se baseiam no cérebro humano. ANNs são utilizadas na resolução de problemas que envolvam tomada de decisões e identificação de padrões, e são particularmente úteis na resolução de problemas não lineares com uma base de dados ampla cujo mecanismo interno não é conhecido de forma satisfatória. ANNs se destacam dos métodos convencionais devido à sua facilidade de modelar sistemas não lineares complexos a partir de uma base de dados, seu desempenho superior em muitas aplicações, sua adaptabilidade e capacidade de processar uma grande quantidade de informações. No entanto, a utilização de ANNs também apresentam diversas dificuldades tais como o alto custo computacional, a necessidade de extensas bases de dados para operar, sua natureza Black Box e a falta de padronização. Atualmente, uma aplicação de destaque para ANNs é na detecção de traços de satélites e detritos espaciais nas imagens astronômicas, que podem ser utilizadas na identificação dos objetos em órbita, detritos não catalogados e melhor compreensão do ambiente orbital.

Palavras-chave: AI. ANNs. Redes Neurais. Adaptabilidade. Detritos.

1 INTRODUÇÃO

The human brain was a revolutionary invention of nature. Since the beginnings of humanity, human ingenuity has enabled the creation of new technologies that have helped humankind take control of the world around it, improve its quality of life and thrive as a species, from bone knives in prehistoric times to modern computers, capable of performing complex calculations in just a few seconds. However, despite the fast development of technology over the last decades, technology is still very limited compared to nature. The most advanced computer available still cannot perform tasks that even the brains of small animals are able to perform with ease. For example, humans can recognize a place they have been to, even if some elements have changed. In contrast, conventional digital computers still struggle to recognize even simple patterns, let alone generalize those patterns to other contexts (Kohli, Miglani & Rapariya, 2014).

Several studies have been conducted in an effort to create computers that operate more like the human brain, capable of interacting with the outside world, recognizing patterns and learning from experience. This field of computer science is known as Artificial Intelligence (AI).

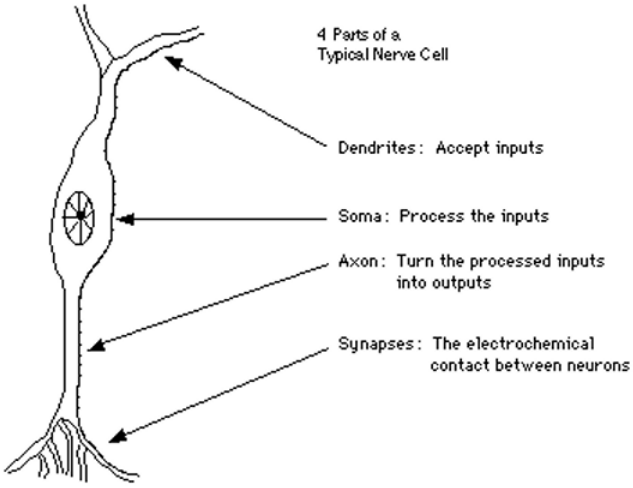
An Artificial Neural Network (ANN) is a tool within the field of Artificial Intelligence. ANNs are designed based on the structure and functioning of the human brain to perform specific tasks, using electronic components or computer simulations (Haykin, 2009). Nowadays, neural networks are mainly used to solve classification problems, identify patterns, approximate functions (modeling), as well as for control and optimization problems, among others.

2 FUNCTIONING OF ANNS

Inside the human brain, there are billions of neurons responsible for the efficient processing of information, received continuously from the environment and from the body's own internal functions. As shown in Figure 1, each neuron is composed of four main parts: dendrites, soma, axon and synapses. Dendrites act as input channels for electrical signals, which are transmitted to the soma, where they are combined and processed. The result is transmitted to other neurons through the output channel, axon, and connections between neurons, called synapses. These connections form a three-dimensional complex network, such that each neuron can create an almost unlimited number of connections (Kohli, Miglani & Rapariya, 2014). In the learning process, new

connections are formed and existing ones can be strengthened. The ability of the brain to change its internal structure makes it highly adaptable and well-suited to solving a wide range of problems.

Figura 1 - Ilustração esquemática de uma célula nervosa típica.



Fonte: (Kohli, Miglani & Rapariya, 2014).

The mechanism behind Artificial Neural Networks follows the same principles as the functioning of the human brain, but in a much more simplified form. Within ANNs, there are processing units called “nodes”, which act as neurons. Just like biological neurons, each node also has an input channel, through which it receives information from other nodes or the environment, a function that transforms input signals into output signals, and an output channel, which transmits information to other nodes or the environment. Each node is connected to other nodes through links. However, unlike biological neurons, artificial nodes can only form a very limited number of connections. Each link is assigned a weight, which is determined during the training process. This weight alters the signals as they pass through the link.

In the beginning of the training process, the links are assigned random weights and organized in an arbitrary manner. Then, the neural network receives inputs from a dataset whose outputs are known. Even though the details of the learning process vary depending on the architecture of the neural network, in general, as the ANN is exposed to different inputs, the weights assigned to the links change and new links can be created.

For ANNs of the supervised type, at each step of the training process, the network is tested using inputs with known outputs. The resulting outputs are compared

to the expected ones, in order to verify the error. Ideally, the ANN's answer should get closer to the true answer after each iteration.

After training, the validation phase begins, during which the performance of the optimized ANN is evaluated. In this phase, the Neural Network once again receives inputs whose outputs are known and the results are compared to the expected outputs to calculate the error. However, unlike in the training process, the weight values are not modified. If the ANN demonstrates satisfactory performance, with small errors, it can be used to solve problems of unknown outputs.

3 TYPES OF NEURAL NETWORK CLASSIFICATION

Neural Networks may differ in many aspects and, therefore, can be classified in various ways. The intended application and project requirements will determine which characteristics are better suited. Some of the main types of Neural Network classification are:

3.1 Degree of supervision in the learning process

The learning process of an ANN can be classified according to the degree of supervision in: supervised, unsupervised and mixed.

The supervised learning requires an input dataset whose output is known. During training, the Neural Network compares the output values obtained after each iteration to the expected outputs, calculating the error between them. The calculated error is then used to adjust the link weights, reducing the error after each iteration.

On the other hand, unsupervised learning does not require an input dataset with known outputs. The ANN analyzes the data from the dataset, grouping it into categories based on patterns of similarities and differences. Mixed learning lies between supervised and unsupervised learning, combining elements of both approaches.

Classification problems require Neural Networks of supervised learning, while associative-memory problems require Neural Networks of unsupervised learning. For example, a problem that involves the classification of animal species calls for supervised learning, as the ANN needs labeled examples of animals from each species in order to learn their distinguishing characteristics, like color, size or shape. Conversely, a problem aimed at distinguishing between males and females of a given species calls for unsupervised learning, as the ANN can identify in the dataset the

common features within each group and the consistent differences between them, allowing it to categorize animals into one of the two classes based on patterns in the dataset.

3.2 Flux direction

ANNs can also be classified according to the direction of information flow, which can be divided into feedforward and feedback. ANNs of the feedforward type have unidirectional flow of information, starting at the input layer, going through the intermediate layers and ending at the output layer. Feedback ANNs, on the other hand, have more than one information flow direction. For example, the information can flow backward from the output layer to a hidden layer.

3.3 Intermediate layers

Neural Networks can be classified according to the number of intermediate layers they have. An ANN is classified as “shallow” if it has few or, most commonly, only one intermediate layer. If the ANN has many intermediate layers, it can be classified as “deep”.

4 ADVANTAGES OF ANNS

Neural networks are tools capable of solving problems using a provided dataset, even if the mechanism behind the generated data or the way they are related are unclear or unknown. Because they don’t need an understanding of the internal mechanism of the problem to operate, ANNs are powerful tools in the execution of tasks involving non-linear problems. Neural networks enable the modeling of systems that would be too difficult to model using statistical analysis or computer programming, providing better results, in many cases.

ANNs can process a large amount of information available in the dataset. Even if some of the included data is not pertinent to the problem, neural networks are still capable of generating consistent approximations for the model. In other words, they admit a large number of variables in the input vector, even when the relationship of these variables with the dependent variable is predominantly nonlinear. Other methods, such as discriminant analysis and logistic regression, for example, admit only the use of variables with linear nature and which are very relevant to the problem. Finding variables that fit these conditions may require a more in-depth analysis of the

independent variables and their correlation with the dependent variable (Grossi & Buscema, 2007).

Artificial Neural Networks are highly adaptable to changes in the given data, because any changes in the input are reflected in updates to the link weight values during training, enabling the internal structure of the neural network to be continuously adjusted. ANNs can still adapt even with abrupt changes in the input data, although these cases may require more training time.

They can also be designed to operate in parallel, which enables higher processing speed, an essential feature for applications that require real-time problem solving (Qamar & Zardari, 2023).

5 CHALLENGES IN THE APPLICATION OF ANNS

Even though the capacity to process large volumes of data, relevant or not to the problem, may be considered an advantage, inclusion of large amounts of irrelevant data contributes to the generation of noise, which interferes with the training process of the neural network. As a result, the model's accuracy may be compromised and its performance may be comparable to the performance of other conventional statistical methods.

Using a system to select pertinent input variables can reduce the noise generated and improve the performance of the neural network. However, developing such a system is not a simple task, because it's necessary to dive deeper into the relationship between the variables from the database and the dependent variable. Preprocessing techniques, such as noise removal techniques, may be used to accelerate convergence and improve its performance, however it increases the operational cost (Basheer & Hajmeer, 2000).

An ANN's ability to generalize the information obtained from the dataset depends on the size of the dataset. The dataset must be large enough to capture the full range of possible variations. If the dataset is not large enough, the learning process is conducted deficiently, which results in an inferior performance, prone to errors. As a result, it may be necessary to conduct more experiments or simulations to expand the dataset, which significantly increases operational and computational costs.

A reliable method to estimate the minimum required database size has yet to be developed. Even though there are some empirical techniques, they are merely approximations with varying degrees of accuracy and limited applicability to specific

cases. As a result, it's very hard to plan the number of experiments or simulations to be conducted. An exceeding number of experiments leads to a waste of time and resources, while insufficient data may result in poor performance of the ANN.

Balancing the data used in training is another challenge and is particularly relevant for classification problems. If a class is better represented than others in the inputs, the neural network tends to favor that class, leading to biased results. Therefore, a thorough inspection of the dataset is essential to identify potential balancing problems, as well as the existence of large values that could overshadow smaller ones. The latter may result in saturation of the nodes, which can slow down the learning process or even prevent the learning process altogether.

The initial link weights are usually chosen arbitrarily due to the lack of a standardized method for choosing them. However, the initial link weights used may have significant impacts on the convergence rate of the ANN, as well as influence the node saturation tendency and contribute to errors that slow down the learning process.

The number of training cycles is another decisive factor for the ANN's generalization capacity and depends on the architecture of the network. While an insufficient number of training cycles can lead to big errors during the test phase, excess training results in loss of generalization capacity and increasing errors during the test phase. Currently, there is still no method able to accurately estimate the amount of training cycles that would result in minimum error, so this number is typically determined through trial and error.

Due to the functioning principle of neural networks, the steps and operations involved in the problem-solving process is unclear in most cases. This is known as Black Box effect and makes it very difficult to understand the underlying mechanism of the problem and detect mistakes. For example, during the process of solving a classification problem, the neural network may detect patterns present in the dataset by coincidence and use these patterns to make misguided classifications. Such an error may go unnoticed due to the Black Box nature of the ANN.

6 APPLICATION TO SPACE DEBRIS

An application for Artificial Neural Networks that has gained increasing importance is the detection of space debris from astronomical images.

Structures on the surfaces of satellites and space debris, such as antennas and solar panels, reflect sunlight and leave bright streaks in astronomical images. The

streaks caused by large space objects or those with high reflectivity can even be observed with the naked eye in the night sky. This phenomenon is considered a form of visual pollution, as it interferes with the natural appearance of the night sky and astronomical observations. In some cases, it’s even necessary to remove the streaks from telescope images. The increasing accumulation of debris in Earth's orbit only aggravates this issue. Nowadays, due to growing awareness of the space debris problem, many satellites are being designed using techniques aimed at reducing their reflectivity and, consequently, the streaks they produce. However, such actions can’t be regarded as solutions to the problem, as they merely help to minimize additional damage.

Even though the phenomenon in question is regarded as undesirable for astronomical observations in general, the streaks carry important information about the presence and positions of satellites and debris in orbit. Using a Convolutional Artificial Neural Network (CNN) to identify the presence of streaks left by man-made objects in telescope images, it’s possible to extract valuable information about the orbital environment, as well as identifying the presence of uncatalogued debris.

In this application, a CNN must be capable of distinguishing between streaks created by artificial space objects and those created by celestial bodies. Such a task can be challenging, especially in the case of low intensity streaks. Moreover, astronomical images are subject to many interferences that hinder the identification of such streaks, such as atmospheric perturbations, cosmic rays and clouds (Elhakiem, Ghoniemy, & Salama, 2023).

The CNN must include filters for processing the input data, in order to reduce noise and improve its performance. Astronomical images used to train the Neural Network include streaks that have already been labeled according to their origins, such that the CNN can learn to identify whether a streak was or not generated by an artificial object.

Even though such applications of Neural Networks have been gaining popularity, many improvements are still needed. For instance, although some methods perform better at detecting low-intensity streaks, most still struggle with detection accuracy. Overlapping of streaks from different sources, as well as the presence of multiple streaks within a single image, also hinder detection accuracy and represent an area that requires further investment.

7 CONCLUDING REMARKS

Artificial Neural Networks are among the most promising technologies today, gaining increasing recognition with the advancement of Artificial Intelligence. ANNs revolutionized the way a variety of complex non-linear problems are solved, offering faster and more practical solutions than would have been possible using more conventional methods. This is largely due to their ability to solve problems without needing to know the mechanism behind it.

However, the lack of standardization in the development of ANNs, as well as a variety of problems that can arise due to characteristics of the dataset, may lead to unpredictable result quality. Some methods can be used to thoroughly inspect the dataset, normalize the input data, reduce noise, correct errors and improve output quality in general. However, implementing these methods can greatly increase operational and computational costs, making ANNs less practical for everyday use and less economically viable.

Therefore, even though ANNs are already present in many applications, such as detection of space debris from telescopes images, this technology still requires further maturing and development. This applies not only to the expansion of ANN capabilities, but also to the standardization of the methods used, in order to facilitate the development of new techniques and enable more effective use of the technology.

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