Engineering Applications of Neuroscience in Artificial Intelligence

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Abstract

For thousands of years, humans have tried to understand the mechanics of intelligence and replicate it on thinking machines. In the early stages of development, human's ambitions to challenge AI in academia kept being crushed. However, in recent years, people have been trying to introduce the working mechanism of the biological brain into the complex calculation method of artificial intelligence, aiming to make the machine perform logical reasoning more elegantly and organically, which has made the field of artificial intelligence achieve rapid development. Every great breakthrough in the history of artificial intelligence has been derived from achievements in neuroscience.

In this paper, we will explain the popular science of the engineering application of neuroscience in the field of artificial intelligence. Aside from the complex mathematical formula derivation process, we will focus on the connections between the biological brain thought processes and neural networks(an extremely popular and effective artificial intelligence technology). In this paper, firstly, the history of artificial intelligence and the profound impact of neuroscience in this field are introduced. Secondly, the realization process of neural network will be explained elegantly and calmly through some relatively easy but exciting mathematical ideas. And then, the magical thinking ability and inference ability of the neural network are demonstrated through several specific application examples. Finally, the development of neuroscience in the field of artificial intelligence is summarized and prospected.

Keywords: artificial intelligence; neuroscience; neural networks; algorithm; model

I. Introduction

Artificial intelligence [1], neuroscience [2] ...... One by one, words rich in modern electronics (explained in Table 1) have time and again brought new sensations to our brain and new understanding of life. However, the more this happens, the more we need to go back to history to find answers, hoping that in the ruins of history, we can find just a few words to unlock the doubts in our minds. Namely, in what follows, we will combine several historical events of artificial intelligence to illustrate its development.

1.1 The history of artificial intelligence has been one of ups and downs, as well as majestic.

1950 Nurture

The real debut of artificial intelligence was in 1950, when Alan Matheson Turing [3], the father of computational science, published "Computing Machinery and Intelligence". In the paper, in response to the question "Can machines think?" Turing devised a game in which a person in one room asks a question and a computer (machine) in another room and another person answers it. If the person who asks the question cannot tell the substantial difference between the two answering the question, then we assume that the computer has the ability to think intelligently. This is the famous Turing test, which has been the accepted standard for judging artificial intelligence until today. In fact, Turing's ideas have profoundly influenced the development of artificial intelligence, and we will introduce a movie "The Imitation Game" based on the true story of Turing's life to show the fascinating ideas and historical contributions of artificial intelligence in the following content.

1956 Birth

In 1956, also known as the first year of artificial intelligence, McCarthy, Minsky and other scientists met at Dartmouth College to discuss "how to use machines to simulate human intelligence", McCarthy proposed the formal adoption of the term "Artificial Intelligence (AI)", marking the birth of the discipline of artificial intelligence, the conference, McCarthy is therefore known as the father of artificial intelligence.

Table 1: Artificial intelligence-related terminology and explanations

Artificial Intelligence Terminology	**Explanation and Definition**
(network) model [4]	Mathematical model. It can be understood as f in the function $y = f(x, c)$, while x is the input to the model, c represents the intrinsic parameters of the model, and y is the computed output of the model
Neural networks [5]	A class of mathematical models inspired by neuroscience
(Optimization) algorithm [6]	An algorithm is interpreted as "any method of solving a problem". We redefine it here as a computational method for solving the model parameter c
Machine Learning [7]	A generic term for a class of models that can solve for model parameters from data
Deep learning [8]	A collective term for a class of deep neural networks and their improved versions

1956-early 1960s Sprouting

Within this phase, artificial intelligence has seen its first high point in the development process. Research in artificial intelligence has led to many notable achievements in machine learning, theorem proving, pattern recognition, problem solving, expert systems and artificial intelligence languages.

Notably, in 1958, a landmark event, the American scholar Frank Rosenblatt proposed the perceptron [9], a single-layer neural network model with variable parameters, which was the first time that human beings expressed the learning function they had in the form of an algorithmic model, and for the first time gave machines the ability to learn knowledge from data and with the ability to reason, it is the prototype of today's neural networks. Since then, the field of artificial intelligence has received a great deal of attention due to breakthroughs in artificial neural network theory, and government agencies have invested large amounts of money to establish many related projects.

1960s-early 1970s Slump

The early breakthroughs in the development of artificial intelligence greatly raised expectations, and people began to try more challenging tasks with some unrealistic R&D goals. However, a succession of failures and the failure of expected goals (e.g., the inability to prove by machine that the sum of two continuous functions is still a continuous function, machine translation jokes, etc.) brought the development of AI to a low point.

Early 1970s – mid 1980s Prosperity

At this stage, computational neuroscience [10] bridged the deficiencies in mathematical theory and computation in artificial intelligence and achieved a major breakthrough in AI from theoretical research to practical applications and from the exploration of general reasoning strategies to the application of expertise. In particular, Werbos proposed the BP (Back Propagation) algorithm [11] in 1974 for parameter computation of multilayer neural networks to solve the problem of nonlinear classification and learning.

Mid-1980s-early 1990s Low Tide

As the application scale of AI continues to expand, the problems of narrow application areas, lack of common sense knowledge, difficulty in knowledge acquisition, single inference method, lack of distributed functions, and difficulty in compatibility with existing databases of expert systems have been gradually exposed. At the same time, the design of artificial neural networks has been lacking corresponding rigorous mathematical theoretical support, after which the BP algorithm was even pointed out to have the problem of gradient disappearance, and therefore could not learn effectively from the front layer. For some time thereafter, artificial intelligence fell back into a situation where no one was interested in it.

Early 1990s - late 1990s Boom

In 1995, one of the most important breakthroughs in the field of machine learning, support vector machine [12] (SVM), was proposed by Vapnik and Cortes under the condition of extensive theoretical and empirical evidence. Since then, machine learning research has been divided into the neural network direction and the support vector machine direction. In the same year, inspired by the human visual system, convolutional neural networks [13] were proposed by Yann LeCun and others, creating a new frontier of artificial intelligence applications in image recognition.

In 1997, IBM's supercomputer Deep Blue defeated the chess world champion Kasparov, which attracted the world's attention.

Late 1990s - Present Outbreak

In 2006, Hinton, a Turing Award winner and one of the three giants of deep learning, proposed the neural network deep learning algorithm, which made neural networks much more capable and started the wave of deep learning in academia and industry at the same time. 2012, AlexNet [14] (a convolutional divine network framework) was extinguished together in the ImageNet challenge, reducing the ImageNet dataset to an error rate of 4.94%, successfully surpassing the human recognition ability (the human eye recognition error rate is 5.1%) and was a historic event for deep learning.

In 2016, Alpha Go[15], a model consisting of three neural networks, developed by Google Deep Mind, won a man-machine battle of Go against Go world champion and professional ninth-degree player Lee Sedol by a total score of 4-1.

In 2018, AlphaFold[16], developed by Deep Mind, predicted 98.5% of the structure of human proteins, following decades of efforts by scientists to resolve protein structures covering only 17% of the amino acids in human protein sequences. This Nobel Prize-winning achievement was published in Nature, where it was highly acknowledged that "this will change everything".

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Artificial intelligence has experienced several ups and downs, each time starting with one impact after another amidst great expectations for new AI technologies, and after hitting insurmountable obstacles, each historic breakthrough has stemmed from achievements made in neuroscience. The brain is one of the most complex systems in the universe, and the great breakthroughs in neuroscience research techniques in recent years have ushered in a new era of artificial intelligence, particularly in the form of neural networks inspired by some of the mechanisms of the human nervous system, which have developed into an unparalleled presence in the field of artificial intelligence.

1.2 How does neuroscience (brain-like science) affect artificial intelligence?

Mankind's relentless quest to understand intelligence, as seen in Descartes' famous phrase "I think, therefore I am" written in 1641, sees intelligence as the essence of life, and the paradox of using our own intelligence to prove the brilliance of our own intelligence, as Lyall Watson famously said "If the brain were simple enough for us to understand, our minds would be too simple to understand the brain". Thinking, in terms of biological evolution, emerged and developed from the human instinct for survival. As the top of the biological chain, human beings need to have a more complex and powerful ability to think, to allocate resources, to optimise their survival conditions, to anticipate and respond to changing threats, and for this reason they have evolved a unique brain nervous system capable of constantly generating and using intelligence. Neuroscience is the study of the neural mechanisms of thought, and at its heart is the study of the activity of neurons in the cerebral cortex and the relationship between the electrical impulses that fly between them and the activity of thought.

Based on research in neuroscience, an important area of research in the field of artificial intelligence, neural networks account for almost 90% of artificial intelligence methods. The idea is based on mathematical modelling of the human nervous system and the design of corresponding neural networks by simulating the propagation mechanism of neural signals in the thinking process of the human brain. In each of these remarkable achievements, such as the Alpha Go mentioned above, large neural networks or their variants were behind them. Feifei Li[17] (member of the National Academy of Engineering, the National Academy of Medicine, the American Academy of Arts and Sciences, and the first Sequoia Chair at Stanford University), the inventor of ImageNet and ImageNet Challenge, has made outstanding contributions to the latest developments in deep learning and AI, yet the basis of these outstanding contributions lies in his research in cognitive and computational He is the inventor of ImageNet and ImageNet Challenge and has contributed to the latest developments in deep learning and AI.

In order to show the line of the article more clearly, here, the organisation of the subsequent content is given.

Part II We will use some simple and elegant mathematical ideas to explain the process of building neural networks, avoiding as much detail as possible about complex mathematical theory. In addition, an introduction to the basic principles of the backpropagation algorithm is given.

Part III We will demonstrate the unique appeal and reasoning power of neural networks through several practical engineering applications. The first two of these examples are interesting applications that we have written code to implement ourselves, and the third is a remarkable contribution that artificial intelligence has made in human history.

In the fourth section we provide a concise summary of the paper and an outlook on the future of neuroscience in artificial intelligence.

II. How to Build a Neural Network

For years, the average person has had a misconception that artificial intelligence is nothing more than using more advanced and complex mathematical instructions to tell a computer what to do, how to simulate human behaviour, and to make the computer 'pretend' to understand human emotions. The cold logic of the machine, with its absolute ones and zeros, never seemed capable of realising the nuanced, organic and sometimes fuzzy processes of the biological brain.

After this, researchers had the bright idea of trying to build artificial brains by replicating the mechanisms by which biological brains work, using ideas from neuroscience. A real brain has neurons, not logic gates. A real human brain has more elegant and organic reasoning, rather than cold, black-and-white, absolute conventional algorithms. Thus, from the original mathematical modelling of neurons [18], to the later proposal of perceptual machines (one-layer neural networks), to later artificial neural networks [19] (artificial neural networks multilayer perceptual machines [20], fully linked neural networks [21]), to convolutional neural networks, recurrent neural networks [22], long and short-term memory networks [23], Transformer [24] Cutting-edge ideas in neuroscience continue to pour into the field of artificial intelligence, causing neural networks to soar and break through themselves, even surpassing humans in some areas at one point.

All of this may sound like a lot of mystery, and one has to ask, what is a neural network? What does it look like? In fact, neural networks, in terms of theoretical establishment, can be represented as a bunch of complex and elegant mathematical formulas, in terms of theoretical implementation, can be represented as a bunch of complex and logical program codes, however, in terms of theoretical engineering applications, it is the common face recognition [25] (belonging to computer vision [26]), speech recognition [27] (belonging to speech processing [28]), text translation [29] (natural language processing [30]), sentiment analysis [31] (natural language processing), driverlessness [32] (part of computer vision [33]) and other examples of close to life applications.

Now, in what follows, we are going to do the exciting thing of building an expert-level "artificial neural network" based on high school mathematics alone, without too much advanced mathematical thinking. This is not an exaggeration or an alarmist statement, but a real, tangible fact.

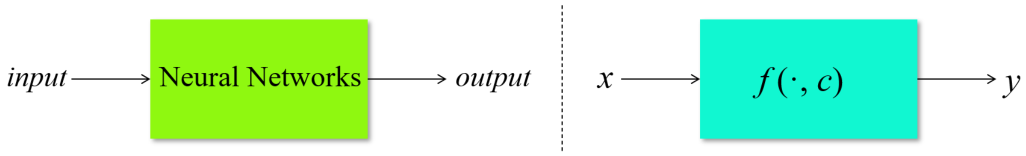

Figure 1. Abstract representation of a neural network (a), mathematical representation (b)

2.1 What does a neural network look like?

Here, we represent the neural network as a box, as shown in Figure 1(a), a black box that, given an input, will compute and produce an output. It is important to remember that all the focus is on the phrase "given input, compute output". We then represent this black box as a function $y = f(x, c)$, as shown in Figure 1(b), where x is the input, y is the output, and $f(\cdot, c)$ is the neural network, and c is an intrinsic parameter of the neural network. That is, if we are given an input x, then the $f(x, c)$ calculated by bringing x into $f(\cdot, c)$ is the output y of the neural network.

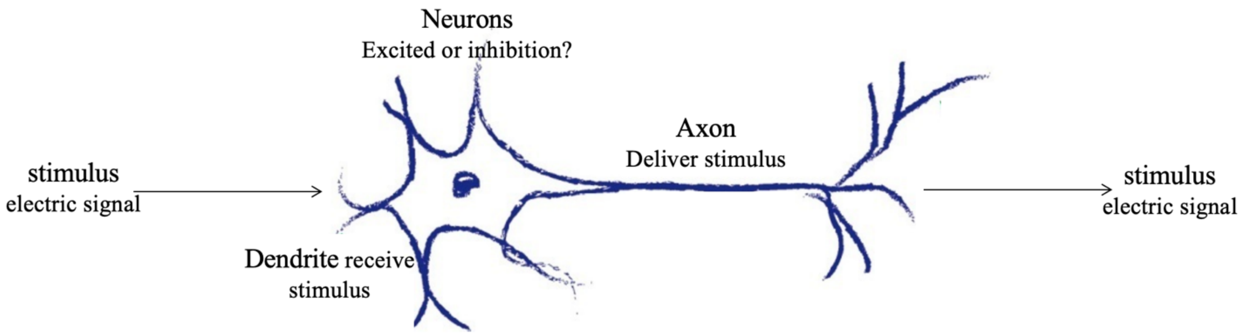

Figure 2. Stimulus propagation mechanisms in neurons

Next, how can we determine the internal structure of this box in the picture above? First, let's look at the basic structure of a neuron, the basic unit in the biological brain, as shown in Figure 2, and see if that sheds any light. Although neurons come in various forms, all neurons transmit electrical signals from one end to the other, along the axon, and from dendrite to dendrite. These signals are then passed from one neuron to another. This is the mechanism by which the body perceives signals such as light, sound, tactile pressure and heat. Signals from specialised sensory neurons travel along the nervous system and are transmitted to the brain, which itself is also largely made up of neurons. It is worth noting that the stimulus transmitted by a neuron from the dendrites to the dendrites of the next neuron is not invariant, and that such signals can be excitatory (signal enhancement) or inhibitory (signal attenuation). Therefore, we consider a mathematical model of a neuron implemented in this way, as shown in Figure 3(a).

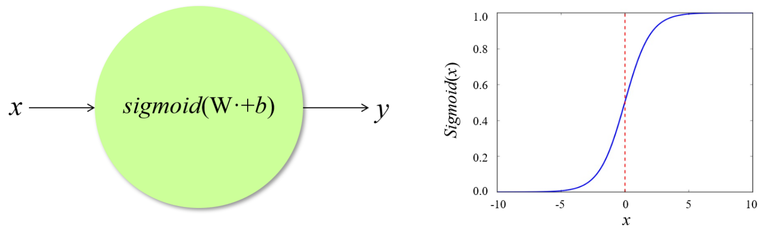

Figure 3. Mathematical modelling of neurons (a) and image of sigmoid function (b)

That is, if our mathematical model of the neuron were to accept an input x, then a linear calculation would first be performed to obtain $W*x+b$, and then the *sigmoid* function would determine to what extent this value would be output, a process similar to the mechanism shown in Figure 2 for controlling whether the stimulus signal is excitatory or inhibitory within the neuron, as shown in Figure 3(b), the image of the *sigmoid* function, see Equation 1, the expression for the *sigmoid* function.

$$sigmoid(x) = \frac{1}{(1+e^{x})} \tag{1}$$

That is, for this neuron, we are given an input x, then he will compute the output y, as in Equation 2.

$$y = sigmoid(W*x+b) = \frac{1}{(1+e^{W*x+b})} \tag{2}$$

In this way, we have implemented a mathematical modelling process for neurons, but it is important to note that we have introduced the parameters W and b of the neuron in the modelling process.

Next, let us look at the form that neural networks take in the biological brain. With our current knowledge of neuroscience in general and brain science in particular, the neurons of the organisms we show in Figure 2, if the signal they receive is strong enough, the neuron will produce an output signal that travels along the axon and reaches the terminal to pass the signal to the dendrites of the next neuron. Figure 4(a) shows a number of neurons connected using this approach.

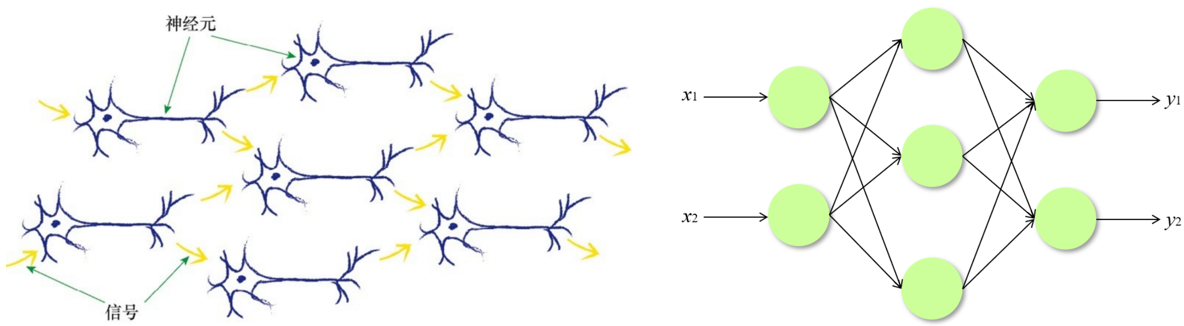

Figure 4. Structure of biological neural network (a) and artificial neural network (b)

We now replicate this natural form in an artificial neural network model by constructing multiple layers of neurons, with neurons in each layer interconnected with neurons in the layer before and after it. Figure 4(b) depicts this idea in detail.

So far, the neural network has taken shape. We can simply understand this as having multiple neurons in each layer, with neurons associated with each other between every two layers (this type of neural network is the most basic neural network and is also known as a fully linked neural network). In the above diagram, for example, this is a three-layer neural network with seven neurons. In fact, the number of layers and the number of neurons in the network are customised and can be changed flexibly. This means that when the input comes in, all the neurons in the first layer will calculate their respective outputs according to Equation 2 above, and these outputs will continue to be used as input to the second layer of the neural network. This process is called forward propagation of a neural network.

In fact, the process of implementing a neural network could be done by computing each neuron one by one as mentioned above, but this would seriously affect the speed of computation. In engineering we generally use matrix computation for forward propagation, which makes full use of the parallel computing power of the computer, but the science of this paper is limited and will not be repeated.

Now, we have implemented forward propagation of a neural network, i.e., given the input to the neural network, the neural network will compute the final output according to the structure shown in Fig. 4(b), although we do not know whether the output is the same as our desired output (target). Next, we refer to the mechanism of human brain learning to make the neural network capable of thinking, in the sense that it can compute not only the output given the input, but also the desired output (target).

2.2 How can a neural network think?

The process of making a neural network capable of thinking is called 'training'. Specifically, we will explain what 'training' is by using a real-life scenario.

Let's teach a child who has just learned to speak to recognise numbers.

First, we prepare 7000 pictures of different handwritten numbers (0-9), of which 6000 pictures are used to teach the child to recognise numbers, i.e. 6000 pictures will be used for 'training' and the remaining 1000 pictures will be used to 'test' the child's learning. "The remaining 1000 images will be used to 'test' the child's learning. Using the first image as an example, we present our 'training' programme in three steps, as shown in Figure 5.

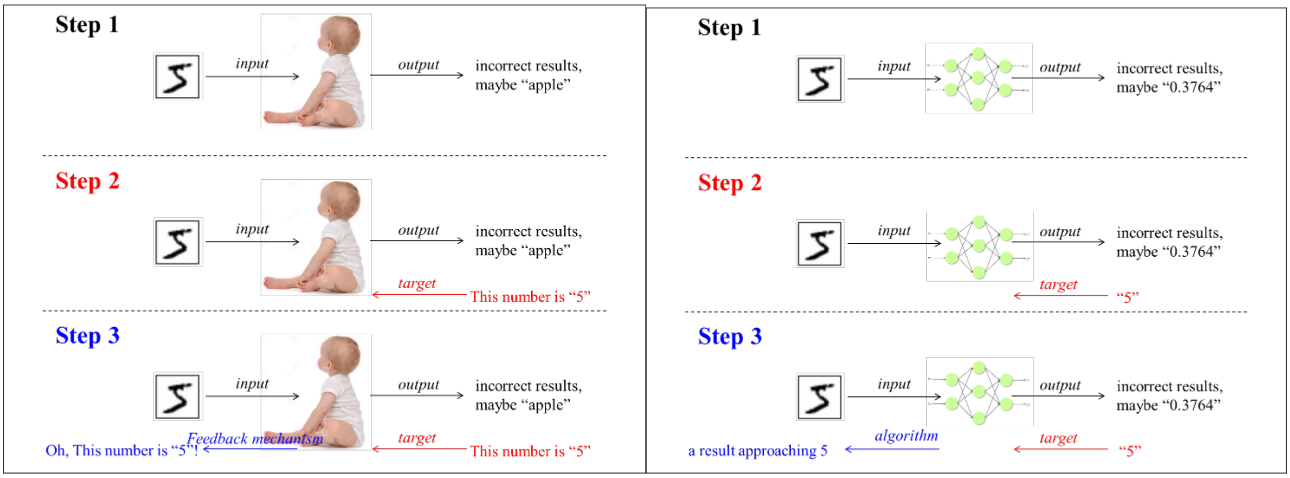

Figure 5. Flow chart for training a child (a) Training steps for a neural network (b)

Step 1, we take out a random image from the 6000 images, as shown in Figure 5(a), which is a handwritten image of the number "5", and the child may say an incorrect result, perhaps "apple" or something like that. This is consistent with the forward computation of a neural network, which, as shown in Figure 5(a), will compute an incorrect output, perhaps "0.3764", because the parameters are randomised during the initialisation of the neural network, and therefore will yield an uncertain output that does not meet our expectations (target). This is because during the initialization process, the parameters of the neural network are random, so we get an uncertain output that does not meet our target.

Step 2, we tell the child that the number is "5". Likewise, for the neural network, we have given this input image a target of 5 in our training.

Step 3, the child receives the correct result, and we believe that some feedback mechanism will be used within the child's brain so that the next time the child encounters a similar image with a "5", he will be able to answer it as accurately as possible. In neural networks, this feedback mechanism is called an algorithm, or an optimisation algorithm, and refers to the use of an algorithm to optimise the internal parameters of the neural network (which are initially initialised randomly) so that the neural network will output the correct result (output=target) as accurately as possible when it receives similar input in the future.

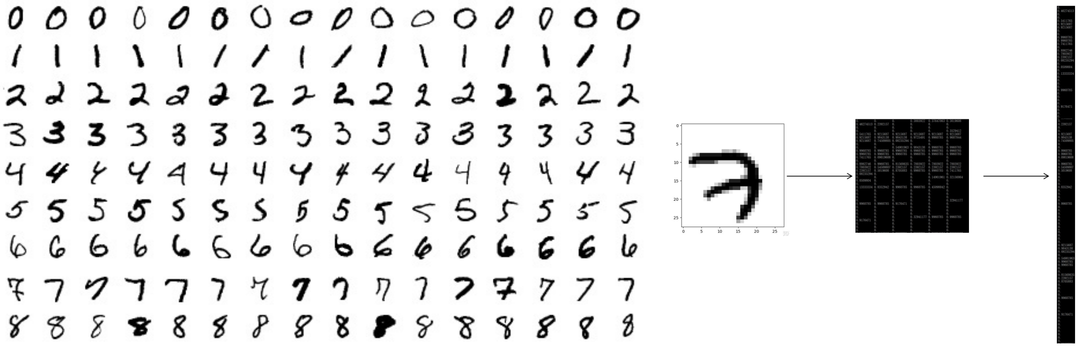

Figure 6. Selected samples from the MNIST dataset (a), per image sample processing method (b)

We then repeat the steps Step1-Step3 6000 times, except that each time the "training" image (input) is a different handwritten digit. Just like the child in the picture, the neural network is able to recognise handwritten numbers at the end of the training.

A neural network is a mathematical model modelled on the structure of the nervous system of a biological brain, which we 'train' to be able to think. However, what is even more mysterious in the 'training' process is the 'algorithm' shown in the diagram, which allows the neural network to automatically adjust its internal parameters by targeting, just as in the training of a child, when the child accepts This mysterious power allows the neural network to automatically adjust its internal parameters through target, just like the feedback mechanism that takes place inside the child's brain when it receives the correct answer from us. However, the focus of this article is on science and space, so we will not go into the details here. We just need to understand that such algorithms are often based on a back-propagation mechanism that automatically adjusts the parameters of the neural network so that it can calculate the result as accurately as possible to approximate the target.

Now, in general, both the child and the neural network have the ability to recognise handwritten numbers, and we will test them on the 1000 images used for the 'test', but we will not tell the child and the neural network the correct We will test them on the 1,000 pictures used for the 'test', but in the process we will not tell the child and the neural network what the correct outcome (target) is.

III. Engineering Applications of Neural Network

In this section, we will demonstrate the unique appeal of neural networks using several practical, interesting and even contributing application examples.

3.1 Handwritten digital image recognition

First, an introduction to the dataset, the MNIST (Mixed National Institute of Standards and Technology database) dataset, is a large database of handwritten digits collected by the National Institute of Standards and Technology, as shown in Figure 6(a), which contains a training set of 60,000 examples and a test set of 10,000 examples. In other words, we will train our neural network with 60,000 different digit images and then observe the neural network's recognition on 10,000 untrained test sets.

It is worth noting that, in order to mirror the second part as much as possible, we therefore use the most basic and rudimentary neural network for this interesting application. As a result, our neural network does not have the same visual capabilities as a convolutional neural network. But this does not in any way affect our ability to achieve this goal; we only need to do this for images, as shown in Figure 6(b), where we extract and expand each pixel point of each image (greyscale map, 28 × 28) into a one-dimensional 784-pixel data.

```python
'''

                                        Neural Network.py
                                            2021-07-27
                                        written by  Zhang Hui

'''

import numpy
# scipy.special for the sigmiod function expit()
import scipy.special
import matplotlib.pyplot

# Neural network class definition
class NeuralNetwork:

    # initialise the neural network
    def __init__( self , inputnodes , hiddennodes , outputnodes , learningrate ):

        # set number of nodes in each input, hidden, output layer
        self.inodes = inputnodes
        self.hnodes = hiddennodes
        self.onodes = outputnodes

        # learning rate
        self.lr = learningrate

        # link weight matrices, wih and who
        self.wih = (numpy.random.rand(self.hnodes, self.inodes)-0.5)
        self.who = (numpy.random.rand(self.onodes, self.hnodes)-0.5)
        self.wih_1 = numpy.random.normal(0.0 , pow( self.hnodes , -0.5) , (self.hnodes,self.inodes))
        self.who_1 = numpy.random.normal(0.0 , pow( self.onodes , -0.5) , (self.onodes,self.hnodes))

        # activation function is the sigmoid function
        self.activation_function = lambda x : scipy.special.expit(x)

        pass

    # train the neural network
    def __train__( self , inputs_list , targets_list):

        # convert inputs list to 2d array
        inputs = numpy.array(inputs_list, ndmin=2).T
        targets = numpy.array(targets_list, ndmin=2).T

        # calculate signals into hidden layer
        hidden_inputs = numpy.dot(self.wih, inputs)

```

Figure 7. Part of the Python code used to implement the neural network

Figure 8. Selected results of the neural network training process

Next, we give some details of the training process of neural networks. In fact, scientific research on neural networks tends to place more emphasis on the evaluation of the final test results, whereas here, given that this is a popular science article rather than a scientific paper, we place more emphasis on the performance of the neural network during the training process than on a few performance evaluation metrics. As shown in Figure 8, we have taken some samples (1-48, 100-148, 1000-1048, 10000-10048) of the recognition results during the training process of the neural network. From Figure 8, we can clearly observe that as the training progresses, the neural network for the learning ability continues to strengthen and can increase the recognition rate.

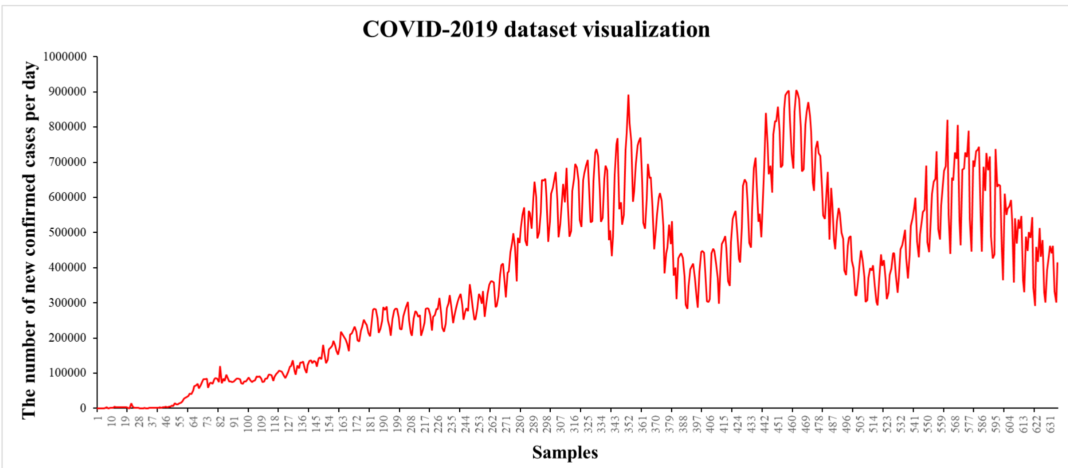

Figure 9. Visualisation of the COVID-2019 dataset

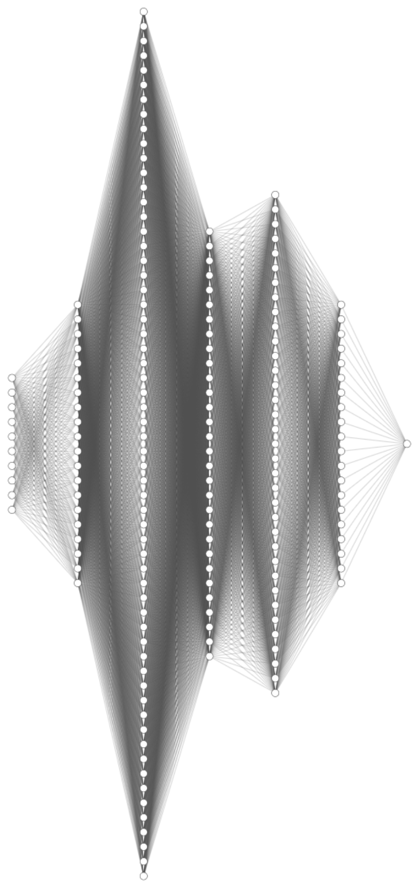

Figure 10. Structure of the neural network used to implement the COVID-2019 forecast

Again, we are concerned about how our neural network performs without being told the correct target, and in what follows we report on the performance of the neural network during testing. The final results calculated from running our code show that the neural network we designed achieved 97.09% on the 10,000 test images dataset. What does this mean? Our neural network correctly recognised 9709 handwritten digital images on his untrained sample of 10,000! This figure is reassuring, and although today's state-of-the-art neural networks have already achieved the highest level of 99.99% on the test set, we have demonstrated through our efforts the effectiveness of the neural networks described in this paper for the image recognition problem.

3.2 COVID-2019 Forecast

Next, we are using neural networks to do something very interesting: the outbreak of pneumonia caused by a novel coronavirus in December 2019, which is rapidly spreading around the world. We are acutely aware that leveraging our expertise will help prevent and control the outbreak, and to this end, we have used neural networks to predict trends for COVID-2019.

First, we downloaded the public dataset of the 2019 New Coronary Pneumonia outbreak from the Hopkins University website and split it into a training set and a test set, on which the neural network was trained and the test set was used to observe the performance of the trained neural network. Figure 9 shows all samples of the dataset, which is the global daily additions for nearly six hundred and thirty days since the outbreak of the novel coronavirus pneumonia outbreak COVID-2019. In addition, we used NN-SVG to map the structure of the neural network we designed, as shown in Figure 10.

In achieving this, we used nearly 400 data for training and tested the prediction of our neural network on a sample of 200. In Figure 11, we present the prediction results of the neural network, which show that the neural network has the ability to predict the number of new confirmations of COVID-2019 and shows good results in curve fitting, although the individual local prediction accuracy is not very high, but we believe that the neural network can at least put the trend of COVID-2019 into prediction.

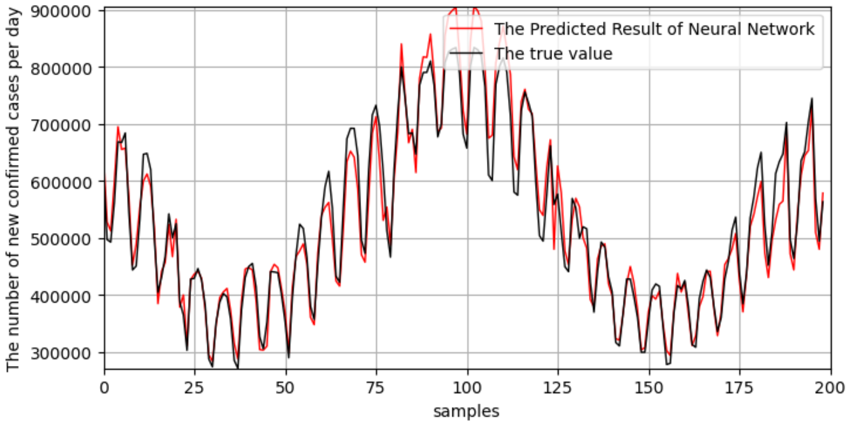

Figure 11. Prediction results of the neural network

Indeed it is, neural networks are so exciting! Yet there is much more to him than that, the artificial intelligence technology represented by neural networks may have the great verve to change history!

3.3 Imitation games

This time we turn our attention to the European theatre of the Second World War, when the Germans invented a new encryption technique, at the same time as the Allied battalions of Britain and the Soviet Union were losing ground, as detailed in the film The Imitation Game. Deciphering the German code was imminent, but it would have taken nearly a century to decipher this new encryption by manual calculation or exhaustive enumeration alone. Turing, the genius mathematician and father of computer science, was tasked with leading a team in the code-breaking effort (shown in Figure 12). Perhaps it was a stroke of brilliance, or perhaps it was just a case of a lot of work, that led Turing to creatively develop the idea of machine learning, which in fact did not exist at the time, and which was not proven to be a neural network, but which we believe is similar to a neural network in that it consists of input and output and its own inherent parameters, and that there is a training process.

On 12 November 1940, Churchill was informed by the code deciphered by Turing's machine (shown in Figure 13) that the Luftwaffe would carry out a devastating bombing raid on Coventry Cathedral and the industrial estate in 48 hours. In order to prevent the Germans from discovering that their code had been deciphered and thus continuing to use their encryption with confidence. At an emergency meeting of the British High Command, Churchill made the difficult but wise decision: Coventry would not be reinforced with air defences, the citizens would not be informed, and the city would not be evacuated early, at the expense of a historic city, in exchange for the Germans' confidence in the safety and security of their codes, for the continuity of uninterrupted sources of secret information, and for the final victory in the whole European theatre.

After 11 hours of indiscriminate German bombing, tens of thousands of lives were lost and Coventry was left in ruins. Hitler, with his "triumphalist" hand in the air, became more and more unstoppable, only to die. History sees the smile of victory in the tears of pain and the fire of revenge in Churchill's eyes. Later, with the help of a machine designed by Turing, the Allies shortened the Second World War by two years and turned the tide at a crucial moment, winning the Second World War and, to some extent, changing the world scene.

Turing not only helped to decipher the seemingly impenetrable Nazi code during World War II, but also helped to open up the whole field of artificial intelligence. However, Turing's presentation of this idea did not receive much attention at the time, and even the British military severely criticised the approach, forcing the work to stop for a time. But history has always been kind to these geniuses! Eventually the thinking machine designed by Turing managed to learn the encryption rules of the German cryptography, and although the reasoning within this machine is unexplainable, history has tested the effectiveness and great contribution of artificial intelligence techniques represented by neural networks. John Graham-Cumming, a computer scientist, said, "He was a national treasure and we pursued him until his death."

VI. Summary and Outlook

In this paper, we see neuroscience epitomised in the history of artificial intelligence and present the far-reaching impact of neuroscience in the field of artificial intelligence. With this in mind, we focus on the implementation of neural networks, an application product of neuroscience in artificial intelligence, and demonstrate their practical application in the context of several application scenarios. Throughout the text, we use as little jargon and mathematical formulae as possible and focus on neural network implementations and algorithms; in fact, the applications of neuroscience in artificial intelligence go much further than this, but are beyond the scope of this paper.

Today, neuroscience is blossoming all over the field of artificial intelligence, for example, outperforming experts in adversarial environments, such as the classic Atari video game, the ancient Go board game, and imperfect information games such as poker. Machines can automatically generate synthetic natural images and simulations of artificial languages that are virtually indistinguishable from real-world human languages, translate between multiple languages and create "neuroart" in the style of famous painters.

Then, Tomaso A. Poggio argues that artificial intelligence breakthroughs have come from neuroscience in the past and will do the same in the future. The brain is one of the most complex systems in the universe, and recent technological breakthroughs in neuroscience research have ushered in a new era in human understanding of the brain. However, our research into the neural network mechanisms of brain function, especially higher cognitive functions, is only just beginning, and experimental neuroscience must progress alongside theory and artificial intelligence. Computational neuroscience is also a necessary bridge between the two fields of brain science and artificial intelligence, and the interaction and synergistic innovation between these fields will greatly advance the future of information technology, brain technology and the next generation of supercomputers.

When opportunities arise, they are often accompanied by challenges, and therefore we also need to reflect on them. In fact, neural networks are not interpretable [34], unlike other techniques in the field of artificial intelligence (e.g. fuzzy logic systems [35] and expert systems [36]), a deficiency that will greatly limit the reasoning power and trustworthiness of neural networks [37]. The basic idea of neural networks is to simulate the information processing mechanism of the human brain, hoping to be able to process natural information, especially sound, language, text and images, well, but humans are unable to explain the specific details of neural networks and have only modelled mathematically after the general structure of the human brain, just as humans are unable to explain the knowledge processing mechanism and reasoning mechanism of the brain nowadays.

In the future, by carrying out research on brain-like computing and brain-based information processing networks and computing systems, neuromimetic design and brain-like systems inspired by synaptic connectivity mechanisms of neural networks, large-scale and high-precision neural network-inspired next-generation artificial intelligence algorithms will be realised, neuron-like processors, memories and brain-like computers will be developed, as well as brain-like intelligences and new intelligent robots, so that brain-inspired brain-like intelligence This will enable brain-inspired brain-like intelligence systems to be truly brain-like in information processing mechanisms and human-like in cognitive behaviour, and ultimately surpass human intelligence.

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